# STATISTICAL INFORMATION SYSTEMS IN A MODERN SOCIETY: ROLES, FUNCTIONS, AND SYSTEM DESIGNS

Bo Sundgren

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# Statistical information systems in a modern society: roles, functions, and system designs

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Contribution to Baltic DB'94 -
Baltic Workshop on National Infrastructure Databases:
Problems, Methods, and Experiences

**Abstract.** *Starting from a general discussion of the nature, purposes, and functions of statistical information systems (and systems of such systems), the paper presents some recent developments concerning the design and architecture of such systems.*

## 1 Statistical information systems

### 1.1 The purposes of statistical information system

An **information system** can be generally defined as a system, which helps a number of persons, the **users** of the information system, to establish and maintain their respective mental models, or **mind models**, of a certain piece of reality, the **object system**, or universe of discourse, of the information system. By performing this fundamental task, the information system can help its users to develop an **understanding** of the object system and its subsystems and components, and to plan, implement, monitor, and evaluate **actions** visavi the object system.

A **statistical information system** is an information system, which serves its purposes by providing its users with **statistical information** and related **information services** to (groups of) **statistics users**. The statistics users are assumed to have tasks, which imply needs to

- describe and understand the object system and its subsystems and components; and/or
- plan, implement, monitor, and evaluate decisions and actions vis-à-vis the object system.

Some typical examples of statistics users are

- companies, organizations, and governmental organs, who want to plan, control, and evaluate their activities;
- researchers, who want to develop a better understanding of society and to help to identify and solve problems in society;
- persons and families, who want to plan their own lifes and to participate in democratical processes.

## 1.2 Statistical vs non-statistical usage of information

What is the difference between statistical and non-statistical usage of information? Statistical information is typically used for decisions that may be vaguely described by such terms as "strategical", "management-level", "policy-oriented", if the usage environment is a business or government organization. In a research environment statistical information is typically used for getting an overview of a more or less complex system (sometimes called the universe of discourse or the system of interest), and for formulating and testing hypotheses, and ultimately theories, about this system.

We may describe the typical usages of statistical information as being of a **directive** nature: statistical information gives direction (advice, guidance) to the decision-maker or scientist, but it is usually not the only factor that determines the final conclusions and actions.

As a contrast, non-statistical usage of information is typically much more **operative**. On the basic activity level of a business or government organization, decisions are oriented towards concrete, individual "cases" like the processing of a certain order from a certain customer, or the court trial of a certain person, suspected to have committed a certain crime at a certain time, in a certain place.

To be precise, one should distinguish between *"statistical usage of information"* and *"usage of statistical information"*. Very often, of course, the two go together, but there are also situations, where statistical information is used for non-statistical purposes, that is, information of a nature, which is usually used for directive purposes as those described above, is instead being used for operative, "individual case" oriented decision-making. For example, consider a physician who is treating a patient. He or she may may collect a lot of statistical information about the health condition of the patient. However, the purpose is very operational; the physician should determine (a) from which illness, if any, the patient is suffering, and (b) how to cure the patient. Similarly, in a factory, statistical information may be used for an operational decision whether to accept or reject a certain lot of manufactured products.

There are also many examples of situations where non-statistical information is used for directive decision-making. For example, a politician, who is going to make a decision about how to distribute some government support to different parts of a country, will typically get a lot of statistical information as a basis for the decision. However, most politicians are also likely to be influenced by other types of information, like impressions from having been "on the spot", arguments from lobbyists, and even tactical considerations in view of coming elections.

Thus information, which is of such a nature that we recognize it as statistical information, is typically used for knowledge-formation and decision-making of a nature that we have here labeled as "directive". In other words statistical information is one important type of directive information.

We have also seen that statistical information can be a component in operative decision-making. However, most of the (operative) information used for operative decision-making is of a nature that we recognize as non-statistical.

What then is it in the nature of a piece of information that makes us recognize it as statistical information? This is a question of semantics, which will be addressed later in this paper. Before going there we shall look at some further properties of statistical information, which are connected with its usage.

The activity or process where certain operative information is used is typically also the source of the information. Thus there is a short distance between the birth and usage of operative information. Moreover, the link between the source and usage of operative information is usually very direct and explicit: the information is collected for a very well defined need, and this need is both a necessary and sufficient reason for the information collection. Thus it is both desirable and feasible to tailor the definition of the information in accordance with the one and only need for it.

As a contrast, the need for statistical information (as well as for other types of directive information) is much more negotiable. It is very seldom that a certain piece of statistical information, defined in exactly a certain way, can be claimed to be absolutely necessary for a certain purpose. In fact, directive decisions can be characterized by the fact that they need no information support at all in order to be taken; the decision-maker can always toss a coin, and whatever the outcome, the operations of the organization will probably continue to work, at least for some time. In the long run directive information is naturally expected to improve the performance of the operations, but the links between the information and its effects are much more complicated and less direct and obvious than in the case of operative information and decision-making.

Operative information can be classified as *"needed"* or *"not needed"* with respect to a certain operation. Statistical information, on the other hand, can at best be attributed a certain *value* for the expected improvement of the quality of a certain decision or set of decisions. This value has to be balanced against the *costs* for the acquisition of the information, that is, the costs for observation, measurement, and processing that is necessary for making the information useful.

Sometimes it is only through the pooling of several needs that the costs for the acquisition of statistical information can be justified. Such situations are called **"multi-purpose"**, since the statistical information collected will be used for several purposes. The conceptual design of multi-purpose information is complicated, since the different information needs are not necessarily compatible. "Common denominators" must be found, and costs must be kept down.

Because of the "multi-purpose" property of statistical information, and since the cost of producing certain statistical information will essentially be the same, regardless of how many times and by how many users that it is used, statistical information will often have the prerequisites for being - in a genuine sense - a so-called **collective good**.

## 2 Semantical aspects of statistical information

Semantics is a research area within informatics and computer science that is receiving growing attention. There are many different names for this subdiscipline: conceptual modelling, infological modelling, semantical modelling, and knowledge representation, to mention some of them.

Problems having to do with the contents and meaning of information have received a lot of attention in statistical organizations, even before computers were introduced. This is not surprising, because it is often more difficult, and at the same time more critical, to define the meaning of statistical information. Why? The answer has to do with what we discussed in the *previous section, the usage and purpose of statistical information.*

The meaning of operative, non-statistical information is often very obvious and clear for its users. Most statistical products of statistical organization are multi-purpose to some extent, very often to a great extent. This is one reason for statistical organizations becoming interested in the semantical aspects of information even before the age of computers. For example, statistical organizations, both national and international, have a long tradition in developing standard definitions, classifications, nomenclatures, code lists, and registers, in order to improve the compatibility, comparability, and usefulness of statistical information.

## 2.1 OPR/ER methodologies for conceptual modelling

The semantics of information has to do with the relation between (a) the symbols and messages that constitute information, on the one hand, and (b) the reality and parts of reality that the symbols and messages refer to, on the other. Thus in order to develop a model of the meaning of a piece of information, we must be able to describe how the piece of information and its parts are related to the piece of reality that the information refers to. One type of conceptual framework, which has become rather popular for doing this is the so-called **Entity-Relationship (ER) model**.

The Entity-Relationship model is often ascribed to Chen (1976). However, it is a fact that similar conceptual models, originated by several European authors, had been presented and used for at least a decade before the appearance of Chen's paper; for example, see Langefors (1966), Sundgren (1973, 1974), Durchholz and Richter (1974), Lindgreen (1974). The methodology used at Statistics Sweden was called the **infological approach**, or the **Object-Property-Relation (OPR) model**, later extended to the Object-Property-Relation-Event-Message (OPREM) model; see Malmborg (1982).

Conceptual modelling according to OPR or ER approaches have not particularly emphasized the properties of statistical information. On the contrary most variations of these modelling methodologies have focused on the type of factual information about individual objects that is typical for operative or administrative information systems. This does not mean that OPR/ER approaches cannot be used for analyzing and modelling statistical information. However, there are still needs to refine some of the concepts to make these models even more suitable for coping with statistical information. We shall return to this topic.

All OPR/ER methodologies for describing the semantical aspects of information are based on three fundamental concepts: **objects** (called "entities" in Chen's approach), **properties**, and **relations** (relationships). In some approaches a fourth concept, **time**, can also be regarded as fundamental. The methodologies assume that any piece of reality that is informed about by some collection of information can be conceptualized and modelled in terms of these basic concepts.

Now we shall turn to the problem of how to extend OPR/ER methodologies in order to make them more suitable for handling statistical information. We shall start with the concept of **statistical characteristic**, or "statistical concept", which has a very central role in statistical theory.

## 2.2 Statistical characteristics

A **statistical characteristic** (cf figure 2.1) is a **property** of a **collective of objects** in the object system. Furthermore, this property, or **variable**, of the collective of objects is a well-defined **function** of one or more properties (variables) of the individual objects in the object collective.

Thus a statistical characteristic can be formally described as a triple

(2.1) $C = <O, V, f> = O.V.f$

where

(i) O is an **object collective**, that is, a set of objects - often called a **population**;

(ii) V is a **vector of variables** (often one single variable), each of which have values for the objects in O, usually one value per object and time value;

(iii) f is a function, a so-called **aggregation function** (like frequency *count*, *sum*, *average*, *correlation*, *variance*, etc); the aggregation function is defined to provide the **true value of the statistical characteristic**, when it operates on the true values of the variables in V for the objects in O.

***Note.*** O.V.f is a useful **dot notation** for the triple <O, V, f>. The dot notation is used in a language called INFOL for describing and manipulating statistical information. For a formal definition of INFOL, see appendix.

## 2.3 Statistical information and statistical data

The term **"statistics"** usually denotes **macrodata** only, that is, "estimated values of statistical characteristics", whereas **"statistical data"** often denotes *both* macrodata *and* the **microdata**, which are used as input to the aggregation process producing the macrodata.

Statistical data are representations of **statistical messages**, which inform about estimated statistical characteristics and underlying observations of object characteristics. Macrodata are representations of **statistics messages**, or **s-messages**. Microdata are representations of **observation messages, o-messages.**

An **s-message** must somehow provide

(i) a *reference to* an **object collective**, $O(t_0)$, which is well-defined in time and space;

(ii) a *reference to* a **vector of variables**, $V = <V(t_1), ..., V(t_n)>$, which have well-defined but usually unknown values for the objects in the object collective at certain specified points or intervals of time, $t_1, ..., t_n$, respectively;

(iii) a *reference to* an **aggregation function**, f, which is well-defined for V;

(iv) a **value**, c', which is the **estimated value of the statistical characteristic**

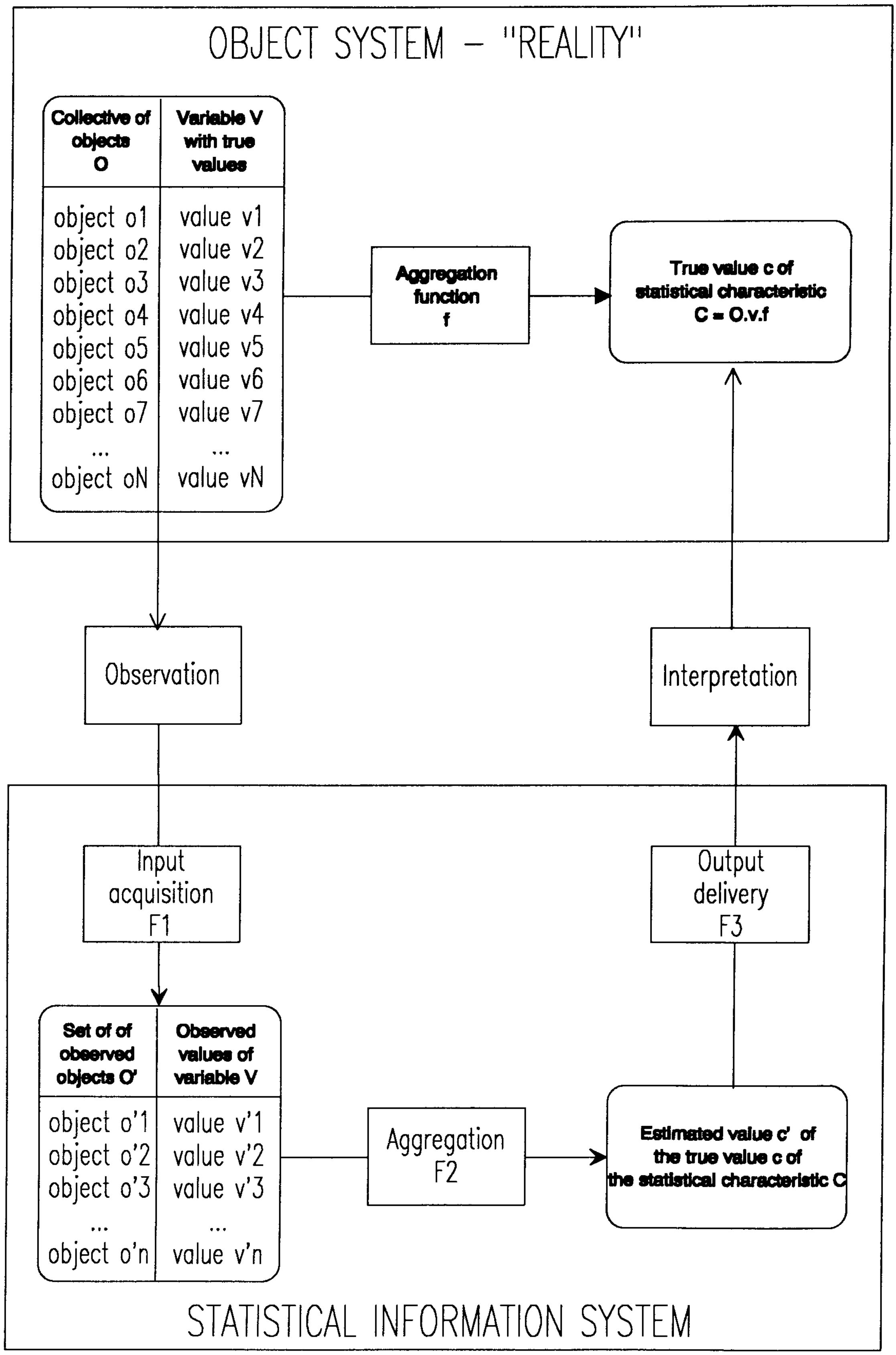



**Figure 2.1.** *Illustration of some fundamental concepts in statistical information processing.*

(2.2) $C = <O(t_0), V(t_1, ..., t_n), f> = O(t_0).V(t_1, ..., t_n).f$

*Note.* An **estimated value** c' of a statistical characteristic C will typically be different from the **true value** c. The discrepancy is due to **errors** and **uncertainties** of different kinds.

An **o-message** must somehow provide

(i) a *reference to* an **object collective**, $O(t_0)$, which is well-defined in time and space, and to which the **observed object** belongs; the observed object may be **identified** or **anonymous**;

(ii) a *reference to* a **vector of variables**, $V = <V(t_1), ..., V(t_n)>$, the **observed variables**, which are supposed to have well-defined true values for the objects in the object collective at the specified points or intervals of time, $t_1, ..., t_n$, respectively;

(iii) a vector of values, $v' = <v'_1, ..., v'_n>$,which are the observed values of V; naturally the observed values may be different from the corresponding true values $v = <v_1, ..., v_n>$.

## 2.4 Structured sets of statistical characteristics and statistical data

Statistical data, particularly macrodata, are often organized in certain typical **structures**. Thus, for example, statistics users are often interested to obtain estimated values of "the same" statistical characteristic for

- a series of time periods (rather than a single one) - **"time series data"**; and/or

- a structured set of object collectives (rather than a single one) - **"structured cross-section data"**.

**Time series data** may be indicated as such by using a **time parameter** as part of the names of the object collectives and variables, which are part of the statistical characteristic. For example, data labeled something like "average income for persons 1991, 1992, and 1993" may be formally described in the following way:

(2.3) $PERSON(t_p).income(t_i).\underline{average}$;

where

$t_p$ = 1991-01-01, 1992-01-01, 1993-01-01;

$t_i$ = the year starting at $t_p$.

The collective of objects, or **population**, referred to in the definition of a statistical characteristic, is often subdivided into sub-collectives, sometimes called **domains of interest**. Such a structured set of related object collectives may be called a **structured population.** The structuring is often accomplished by means of **crossclassification**, using the Cartesian product of the value sets of a number of variables. For example, a structured population labeled

(2.4a) "persons by occupation, age_group, and sex 1991"

may be formally described as:

(2.4b) PERSON(1991)(by occupation(1991) * age_group(1991) * sex(1991));

If we combine the structuring mechanisms of (2.2) and (2.3) we get a rather complex time series of cross-classified cross-sectional data. For example, a set of statistical data labeled

(2.5a) "average income for persons by occupation, age_group, and sex 1991, 1992, and 1993"

may be formally described as

(2.5b) PERSON($t_p$)(by occupation($t_p$) * age_group($t_p$) * sex($t_p$)).income($t_i$)average;

where

(i) $t_p$ = 1991-01-01, 1992-01-01, 1993-01-01;
(ii) $t_i$ = the year starting at $t_p$.

A generalization of this format for specifying structured sets of statistical characteristics and statistical data is the following **box structure** format, used in the INFOL language:

(2.6) <object type>($t_o$)[(with <property>)]
[(by $vg_1(tg_1)$ * ... * $vg_n(tg_n)$)].
(($vb_1(tb_1)$, ..., $vb_m(tb_m)$)).<aggregation function>;

where

(i) <object type> denotes a **time-independent** object collective, which is made **time-dependent** by means of the qualifier ($t_o$), which may be either a parameter (in the case of a time series) or a constant;

(ii) the optional clause [(with <property>)] indicates a **selection** of a subset of <object type>($t_o$) by means of <property>, which may be expressed in terms of variables variables, which are defined and relevant for the objects in the object collective;

(iii) the two clauses described in (i) and (ii) form a part of the box structure, which is sometimes referred to as the **alfa part**;

(iv) the value sets of the so-called **gamma variables**, $vg_1(tg_1)$, ..., $vg_n(tg_n)$, crossclassify the time-dependent object collective;

(v) the gamma variables are **time-qualified**, and any one of the qualifiers may be either a parameter (time series case) or a constant;

(vi) the variables $vb_1(tb_1)$, ..., $vb_m(tb_m)$ are the so-called **beta variables**, which are also time-qualified (by means of parameters and/or constants), and the values of which are aggregated by means of <aggregation function>.

*Note 1.* In practice, many of the time parameters (time constants) occurring in a box structure expression are actually the same, and then they may be separately specified in a special time clause, sometimes referred to as the **tau part**.

*Note 2.* Box structures following the format given above are sometimes referred to as **alfa-beta-gamma-tau-structures**.

## 2.5 Object classifications and generic hierarchies

In the original versions of OPR/ER methodologies there were only the two levels of abstraction that result from the instance/type distinction principle. Over the years, starting with Smith & Smith (1977), several additional levels and dimensions of abstraction have been identified, which facilitate a semantically richer analysis and modelling of information.

We have seen that the instance/type abstraction applied to objects is essentially a classification of object instances into object types. There is no reason why a classification process could not be repeated in such a way that we get an n-level **classification hierarchy**. Such classification hierarchies are alternatively called **generalization/specialization hierarchies** or **generic hierarchies**. For example, the object type PERSON may be specialized into the *subtypes* MALE_PERSON and FEMALE_PERSON, and the object types BIKE, CAR, and BUS may be generalized into the *supertype* VEHICLE.

In generic hierarchies, variables are **inherited** from supertypes to subtypes, and so are properties, which are common for all objects in a supertype. Thus all variables, which are relevant for the object type PERSON, will also be relevant for the subtypes MALE_PERSON and FEMALE_PERSON, and all instances of both subtypes will automatically inherit all properties which are common for all instances of the PERSON supertype, like "having two eyes". On the other hand, the subtype will have certain variables and properties, which distinguish them from other subtypes on the same level in the generic hierarchy. For example, MALE_PERSON may have a variable "military service done?" and FEMALE_PERSON may have a variable "number of pregnancies". Furthermore MALE_PERSON will have the unique common property *sex="male"*, whereas FEMALE_PERSON will have the unique common property *sex="female"*; this implies also that "sex" is a variable (of the supertype), which serves as a **classification key** for the classification into subtypes.

A generic hierarchy may be graphically visualized as in figure 2.2, which also contains the relevant definitions expressed in the INFOL language.

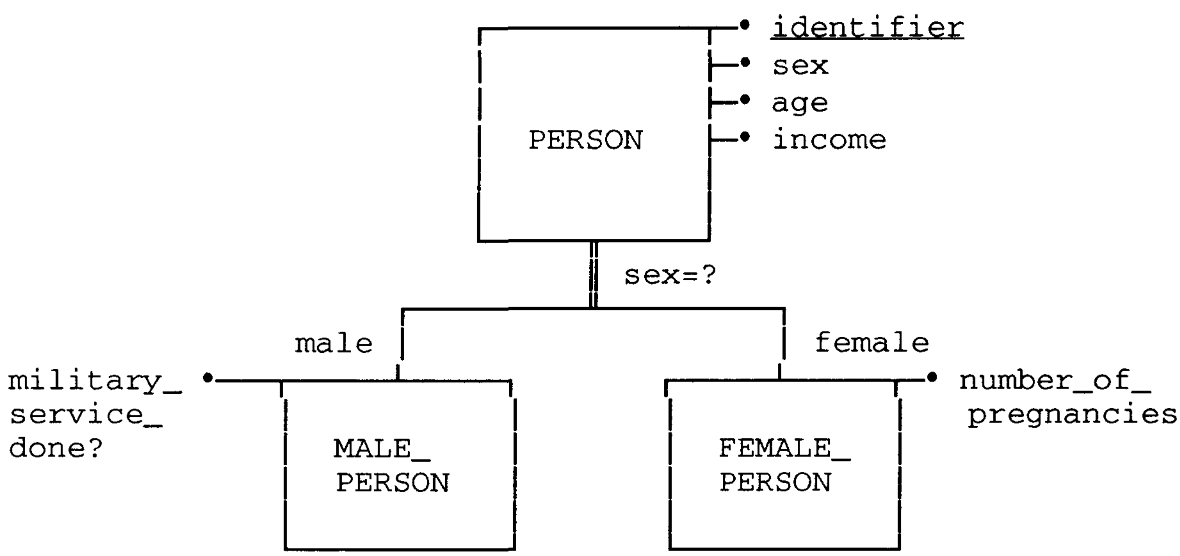
In statistical surveys object classifications and generic hierarchies occur in several forms and for different purposes. For example, within a certain population different subsets of objects, called **domains of interest,** or domains of study, are usually specified. The subsets may be specified one by one (cf INFOL expressions on the form "<object type reference> **with** <property reference>") or as a crossclassification by means of a Cartesian product of variables (cf INFOL expressions on the form "<object type reference> **by** <variable reference>", where the variable reference may be an expression evaluating to a Cartesian product of variables.

*Examples:*

**single subset:** PERSON **with** citizenship = "foreign";

**crossclassification:** PERSON **by** age_group × sex;

Subsets of populations are also specified for **stratification** purposes. Although the purpose is different, the specification of a stratum can formally be expressed in exactly the same ways as specifications of domains of interests.




```
INFOL definitions:

persons_by_sex <--- PERSON(by sex) =
                {MALE_PERSON, FEMALE_PERSON};

MALE_PERSON <--- PERSON(with sex = "male");

FEMALE_PERSON <--- PERSON(with sex = "female");
```

**Figure 2.2.** *Graphical illustration (with accompanying INFOL definitions of the classification hierarchy "persons_by_sex").*

## 2.6 Abstraction by statistical aggregation

It should be noted that there is only one basic collection of object instances which is classified in a classification hierarchy. This abstraction mechnism should be carefully distinguished from another one, which is very typical for statistical information: the **statistical aggregation hierarchy**. (Unfortunately there is again another type of aggregation, which has nothing to do with the statistical concept of aggregation; see Smith & Smith (1977).)

The meaning of statistical aggregation can be described in two steps. The first step is an object classification of any of the types described in the previous section (including the special cases of subtyping and crossclassification).

In the second step of statistical aggregation the instance/type distinction is "moved one level" with respect to the objects and object classes in the object classification hierarchy defined by the first step. This creates "a higher level of abstraction", where the object classes (types, subtypes, and supertypes) in the classification hierarchy will now be regarded as object instances rather than as object types. These "collective object instances" will be called **aggregated object instances**, and the corresponding "collective object type" will be called an **aggregated object type**.

As an example we may consider the classification hierarchy "persons_by_sex" in the previous section. The individual persons are the object instances in this classification hierarchy, and the object classes (populations and domains of interest) "PERSON", "MALE_PERSON" and "FEMALE_PERSON" are the object types, making up a supertype/subtype hierarchy. Applying the statistical aggregation abstraction mechanism to this hierarchy implies a change of perspective, so that the object classes are no longer looked upon as object types (only), but (also) as object instances on a higher level of abstraction. The object type for these collective instances could be called (in this example) PERSON_GROUP. This object type has three instances according to our definitions:

PERSON_GROUP = {PERSON, MALE_PERSON, FEMALE_PERSON};
= {PERSON **by** sex};
= (PERSON **by** sex).**agg**;

The two last lines above illustrate two alternative INFOL formalisms for expressing derivation of object types by statistical aggregation; one uses the set brackets, {...}, and the other one an operator, **agg**, to indicate the aggregation abstraction.

Like other objects the object instances of PERSON_GROUP may have properties, and these properties may be expressed in terms of variables for PERSON_GROUP. The properties and variables of aggregated objects are very often derivable by some type of **aggregation process** (frequency counting, summarization, computing of averages, percentages, variances, correlations, etc) from properties and variables of the object instances on the next lower aggregation level.

Thus aggregation of object types and aggregation of variables often go hand in hand. This is also reflected in the INFOL formalism. Instead of writing

(PERSON **by** category).**agg.count** (or, equivalently, {PERSON **by** category}.**count**);

it is possible to write

(PERSON **by** category).**count**;

In the latter writing an operator like **count** (or **sum**, **avg**, etc), which aggregates the values of a variable for a (possibly classified) set of objects, *implies* a preceding object aggregation, as expressed by **agg** or {...}.

As an example of statistical aggregation we may again consider a group of persons that is classified according to their sex into males and females. As long as we do only this, it is a pure classification hierarchy. As we have seen, the classification can be used for structuring the information into subsets, which are homogeneous with respect to relevant variables and common properties.

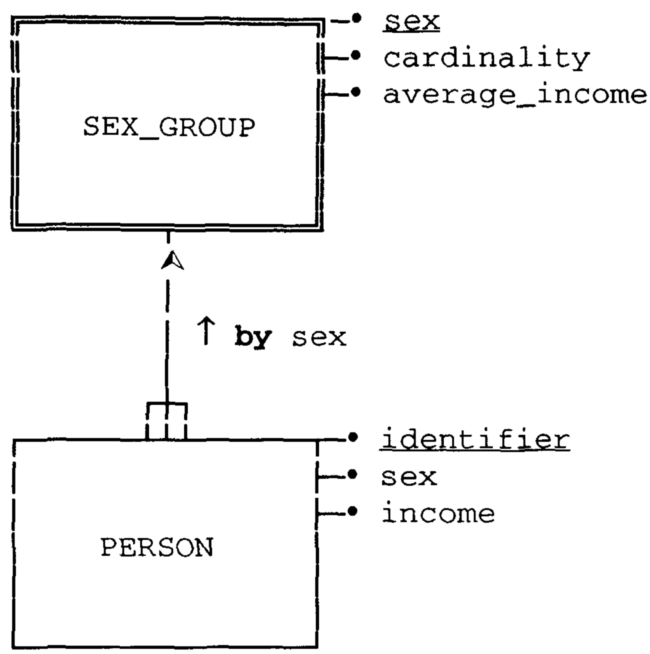
However, we may also start to derive properties of the sexgroups as such, for example by simply counting or estimating the number of persons belonging to each group, or by computing or estimating the average income for each group on the basis of the incomes of (a sample of) the respective person instances. On the lowest abstraction level (aggregation level) the object instances will be persons having incomes. On the next level there will be only two instances: "males" and "females" having their respective cardinalities and average incomes as properties.

An aggregation hierarchy may be graphically visualized as in figure 2.3. The figure also gives some example of the INFOL syntax by showing the definitions for the derivable concepts in the figure.

Abstraction by means of aggregation is one of the most typical semantical features of statistical information. The prefixes *micro-* and *macro-* are often used to distinguish between statistical information before and after aggregation.

In many statistical information systems the input information consists of unaggregated microinformation, whereas the output information consists of aggregated macroinformation. However, this is a rule with exceptions. For example, if a national statistical office collects economical information from companies, this information is microinformation for the survey processing in the statistical office, but for each one of the companies contributing to the survey, the contributed information is likely to be aggregated from numerous economical transactions inside the company.

Thus the *micro/macro* distinction is relative rather than absolute. If microlevel objects are classified and abstracted into macrolevel objects, these object can again be regarded as micro-objects and be subject to classification and abstraction into macroobjects on a yet higher level of abstraction. A special case is if the original classification is a hierarchical classification consisting of more than two levels. An example of statistical aggregation based on a **multilevel classfication hierarchy** is shown in figure 2.4. The figure also shows how such a **multilevel object aggregation hierarchy** can be graphically represented in a more compact way.




**INFOL definitions:**

```
SEX_GROUP <--- {PERSON(by sex)};
SEX_GROUP.sex <--- some PERSON.sex;
SEX_GROUP.cardinality <--- PERSON.count;
SEX_GROUP.average_income <--- PERSON.avg(income);
```

**Figure 2.3.** *Graphical illustration of an aggregation hierarchy; with INFOL definition expressions.*

## 2.7 Value aggregation and hierarchical variables

As illustrated by the last example above, multilevel object aggregation often goes hand in hand with hierarchical variables like region# = county#:municipality#. A **hierarchical variable** is a variable with a **hierarchically structured value set**, and a hierarchically structured value set is a value set, which can be seen as the result of a **value aggregation** process similary to the object aggregation process described in the previous section.

Object aggregation starts with the set of object instances of an object type. Value aggregation analogously starts with the set of values of a value type. The values are classified into subsets of the value set, and each one of these subset is then, after abstraction, regarded as a value "on a higher level". The higher level values are thus defined as an aggregation (= classification + abstraction) of the lower level values.

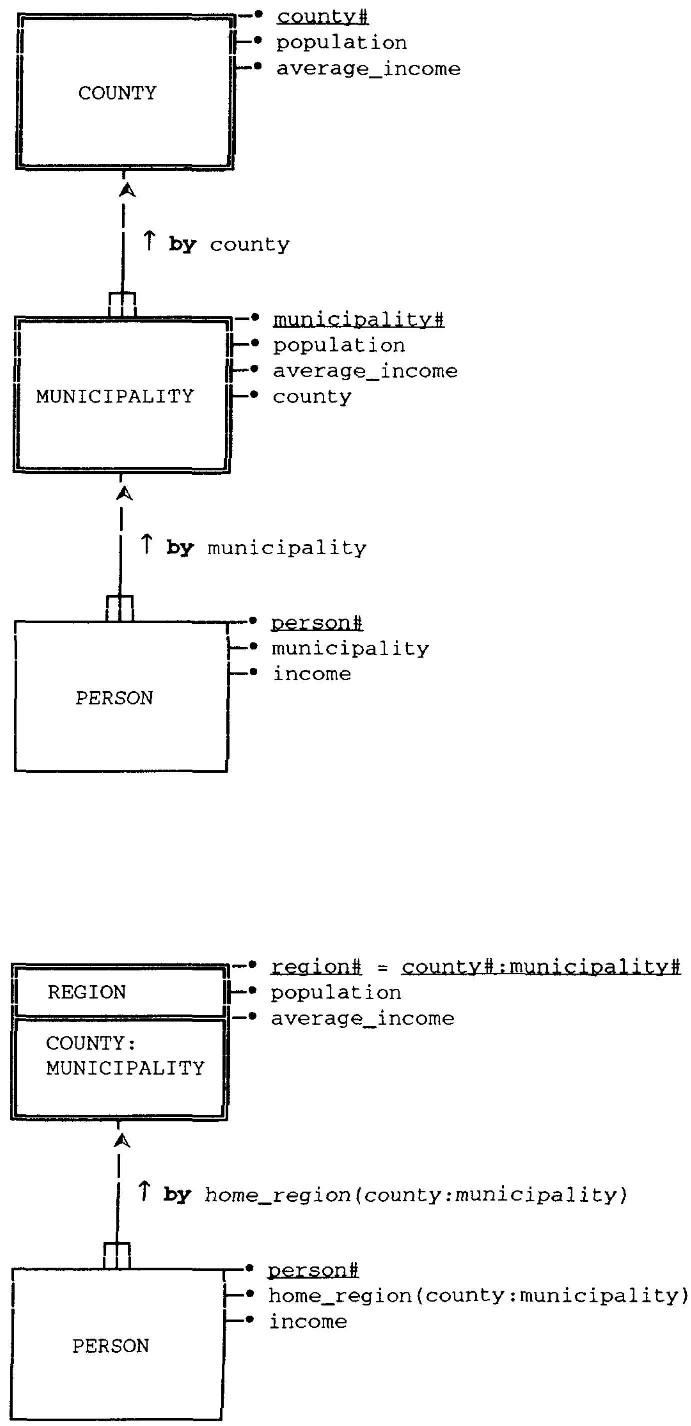



**Figure 2.4.** *A multilevel object aggregation hierarchy.*

For example, suppose that we start with a value type having the value set

V = {1, 2, 3, 4, 5, 6};

and that this value set is classified in the following way:

A = {1, 2, 3}; B = {4}; C = {5, 6};

Now we may abstract the subsets A, B, and C into higher level values of a higher level value set

W = {A, B, C};

which we may write

W = {A{1, 2, 3}, B{4}, C{5, 6}};

in order to indicate the definitions of the higher lever values in terms of the lower level values. By taking the union of V and W we finally get a complete, hierarchically structured value set of two levels:

U = {A{1, 2, 3}, 1, 2, 3, B{4}, 4, C{5, 6}, 5, 6};

We can see that each reference to a higher level value includes the definition of the value in terms of the lower level values. Thus the specification of the new, hierarchical value set includes both the values and the structure between the values. However, the naming convention used here is not very practical. A more practical way of referring to the values, which still retains the structure visible, would be the following one:

U = {A, A:1, A:2, A:3, B, B:4, C, C:5, C:6};

The lower level values are referred to by a "family name", indicating the "parent value" on the next higher level in the hierarchy, and a "first name", indicating the "member of the family". An even more common practice is to rename the low level values, using the fact that the "first names" need be unique only "within the family":

U = {A, A:1, A:2, A:3, B, B:1, C, C:1, C:2};

Now we have finally arrived at the typical pattern for naming values in hierarchical value sets. It is also customary to give a name to a hierarchical value set that indicates the hierarchical structure by having a name component for each level in the hierarchy. Example:

region = county : municipality;

Like in this example, the hierarchically structured name need not be the only name of the value set. Note also that the naming conventions just described actually imply some ambiguity. In the just given example, it is easy to conclude that a region value name consists of two parts: a county value name, and a municipality value name. However, this is in a way both true and not true. As described above, the municipality name would consist of two parts: a "family name", and a "first name". The family name of a municipality value is actually the same as the (complete) name of a county value. Thus the complete municipality value name consists of a complete county value name together with the first name of the municipality; the latter is only unique "within the family". If we call the complete name of a hierarchical value "the long name", and the first name part "the short name", we get:

region value name = county value name : short municipality value name;

long municipality value name = county value name : short municipality name;

However, in practice the term "municipality value name" would often be used ambiguously to denote both the long and the short municipality name. To make it even more concrete: if "region code" consisted of four digits, where the first two digits would identify a county, and the last two would identify a municipality within a given county, the last two digits would probably often be referred to as "the municipality code", although it would only be the short name part of the complete municipality code. This ambiguity is a source of some confusion when discussing hierarchical variables and hierarchically structured value sets.

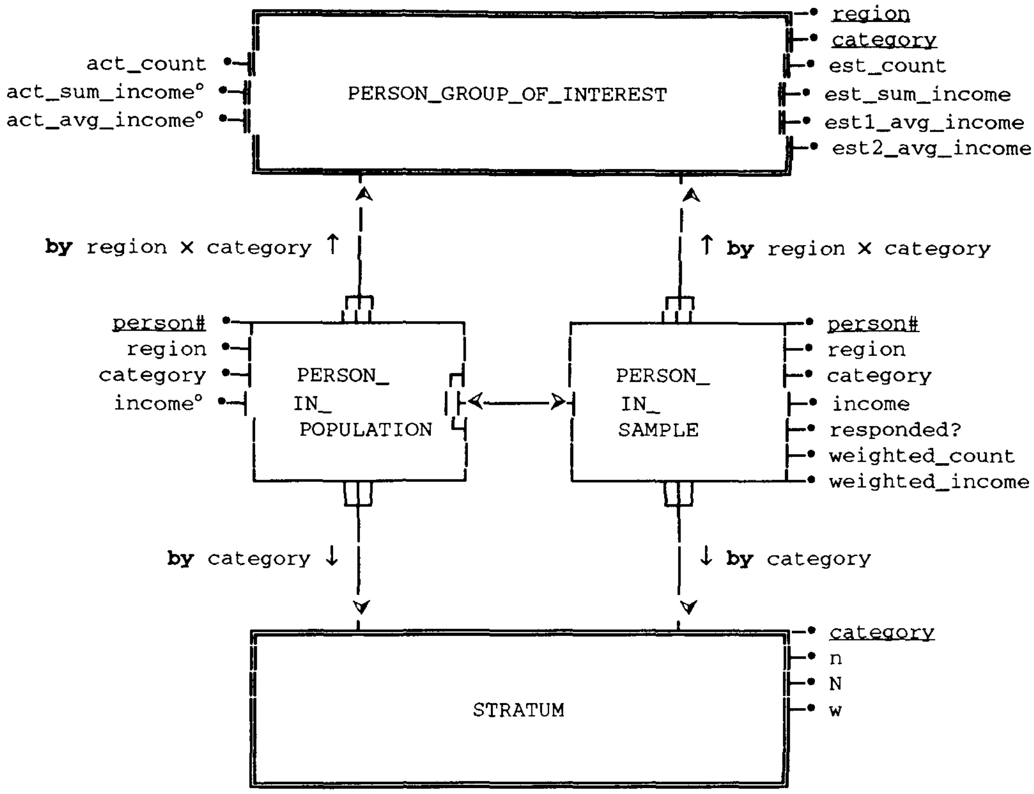
The discussion here about two-level hierarchical variables and value sets can easily be generalized to n levels.

## 2.8 Sampling and estimation

Beside aggregation, sampling is a typical process in many statistical information systems, as well as "the twin process" of estimation based on sampled information. How can we model the semantics of sampled statistical information and of the processes of sampling and estimation? Figure 2.5 illustrates one possible way of tackling these problems, using some of the extensions to ordinary OPR modelling that have been introduced in this paper.

The example used in figure 2.4 is a hypothetical sample survey, where the population is a set of object instances belonging to the object type PERSON. We know the values of some variables for all the instances in the population: *person#*, *region*, and *category*. Population characteristics (parameters) that are functions of these variables can be estimated (computed) by evaluting the function over the object instances in the population. On the other hand *income* is a variable which is assumed to be relevant but not known for the object instances of the PERSON population. Instead it should be estimated after observing a sample of PERSON objects. The sample is supposed to be taken on the basis of random sampling from subsets of the population formed by stratification. Every object instance within a certain stratum has equal selection probability n/N, where n is the number of instances to be selected from the stratum, and N is the total number of instances in the stratum; n/N varies between strata.

The OPR-model for the sample survey contains two object types corresponding to the (generic) object type PERSON: PERSON_IN_POPULATION and PERSON_IN_SAMPLE; there is a partial one-to-one relation between the two object types. The two other object types in the model, STRATUM and PERSON_GROUP_OF_INTEREST, are formed by statistical aggregation of (any one of) the PERSON object types. The formal definitions, expressed in INFOL, can be found in the text under the object graph. The meaning of the object type STRATUM is obvious from the name. The object type PERSON_GROUP_OF_INTEREST is an object type, whose instances are **domains of interest** or **domains of study** in the sense of Marriott (1990), that is, subgroups of the population (including the population as a whole) which are of particular interest for the users of the statistical results derived from the survey.




Derivable object types:

```
PERSON_GROUP_OF_INTEREST = PERSON_IN_POPULATION(by region × category).agg;
PERSON_GROUP_OF_INTEREST = PERSON_IN_SAMPLE(by region × category).agg;
STRATUM = PERSON_IN_POPULATION(by category).agg;
STRATUM = PERSON_IN_SAMPLE(by category).agg;
```

Derivable variables for STRATUM:

```
n = PERSON_IN_SAMPLE(with responded="yes").count;
N = PERSON_IN_POPULATION.count;
w = N/n;
```

Derivable variables for PERSON_IN_SAMPLE:

```
weighted_count = STRATUM.w;
weighted_income = weighted_count * income;
```

Derivable actual variables for PERSON_GROUP_OF_INTEREST:

```
act_count = PERSON_IN_POPULATION.count;
act_sum_income° = PERSON_IN_POPULATION.sum(income°);
act_avg_income° = PERSON_IN_POPULATION.avg(income°);
```

Derivable estimated variables for PERSON_GROUP_OF_INTEREST:

```
est_count = PERSON_IN_SAMPLE.sum(weighted_count);
est_sum_income = PERSON_IN_SAMPLE.sum(weighted_income);
est1_avg = est_sum_income/est_count;
est2_avg = est_sum_income/act_count;
```

**Figure 4.** *An object graph - with accompanying INFOL definitions - corresponding to a sample survey.*

Many of the variables for the object types are derivable from other variables; once again the definitions are stated in INFOL below the object graph. Variables for which data are not available (like *income* for PERSON_IN_POPULATION) are indicated by a small ring (°) after the variable name.

## 3 Major functions of a statistical information system

A statistical information system accomplishes its tasks by performing three major functions:

(F1) an **input acquisition function**, which directly and/or indirectly **observes** (measures) certain **object system characteristics**, and which **prepares and stores** the information thus obtained in the form of data, so-called **microdata**;

(F2) an **aggregation function**, which transforms the microdata produced by the input acquisition function into **macrodata**, or **"statistics"**, which are **estimated values of statistical characteristics.**

(F3) an **output delivery function**, which makes macrodata (statistics) available to the users, and which assists the users to interpret and analyze the data further.

Figure 3.1 illustrates a model of a statistical information system, which contains the three major functions. Figure 3.2 illustrates the result of a deeper functional analysis. The statistical information system in figure 3.1 is assumed to be database-oriented and self-describing. In a **database-oriented statistical information system**, the microdata and macrodata, which are stored and processed by the three major functions (input acquisition, aggregation, output delivery), are communicated within and between the functions via a database. In a **self-describing statistical information system**, the microdata and macrodata are described by means of accompanying **metadata**, which are stored in the database, and which are consistently transformed, whenever the described data are transformed.

A simple example of a statistical information system is a "traditional" **statistical survey.** Another type of statistical information system, which statistical offices are now paying much attention to, are **retrieval systems.** A statistical survey is focusing on a certain data collection process, resulting in a certain collection of microdata, which are aggregated into estimated values of certain statistical characteristics. In contrast, a retrieval system focuses on the needs of a particular category of statistics users, and aims at making available macrodata and microdata from different surveys (and other sources), which may be relevant for the particular category of users.

In addition to statistical surveys and retrieval systems, there are other types of statistical information systems of a more auxiliary nature. One example is **registers** (cf figure 3.1). There are two kinds of registers, which are particularly important for statistical information systems: **base registers** and **code registers.** A **base register** establishes and maintains an authorized list of the objects belonging to a certain population. A **code register** establishes and maintains an authorized list of the values belonging to the value set of a certain variable or classification.

A complex statistical information system may contain many statistical surveys, retrieval systems, registers, etc, as subsystems. "The statistical information system of a country" is an example of such a complex statistical information system.

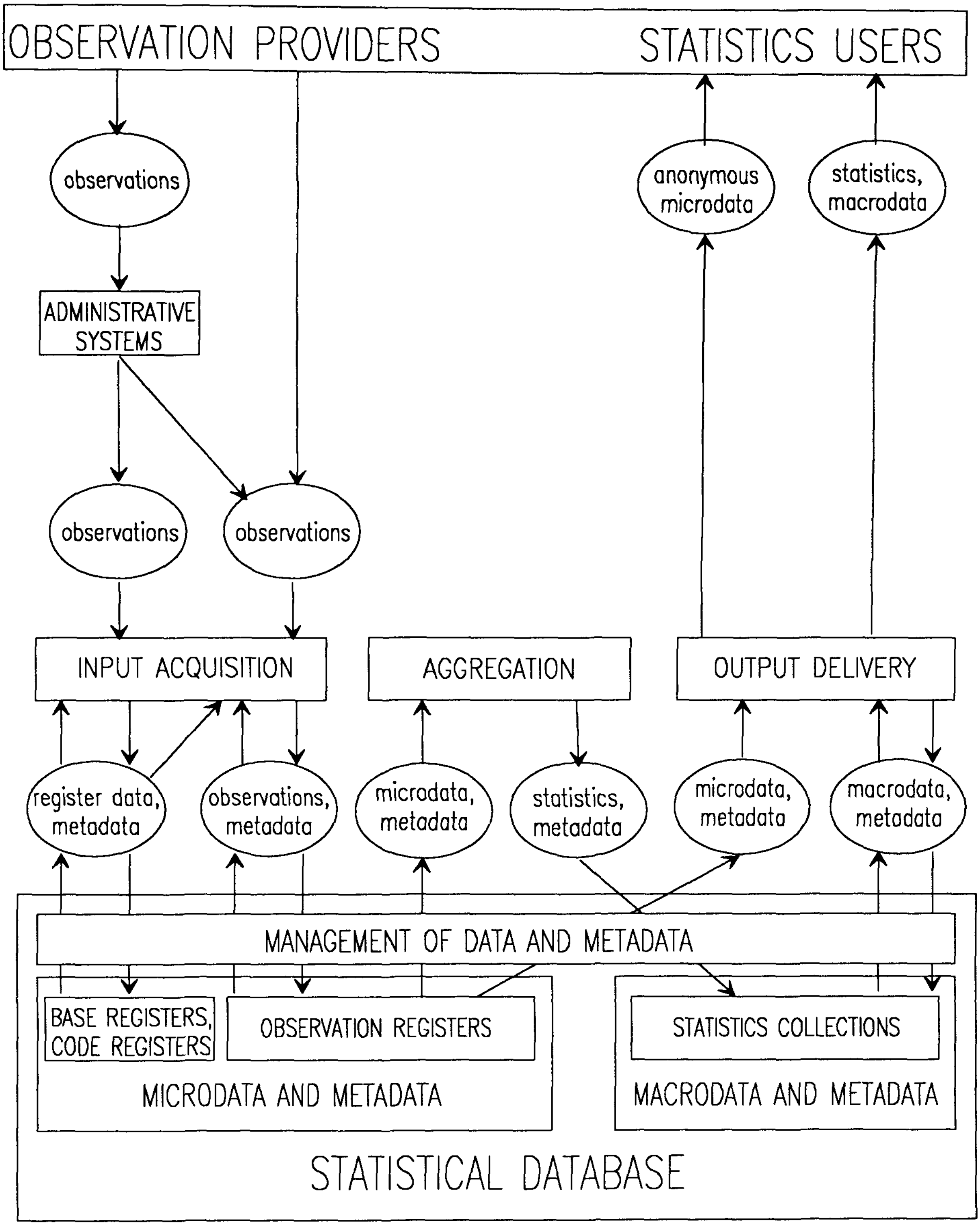



**Figure 3.1.** *A model of a self-describing database-oriented statistical information system.*

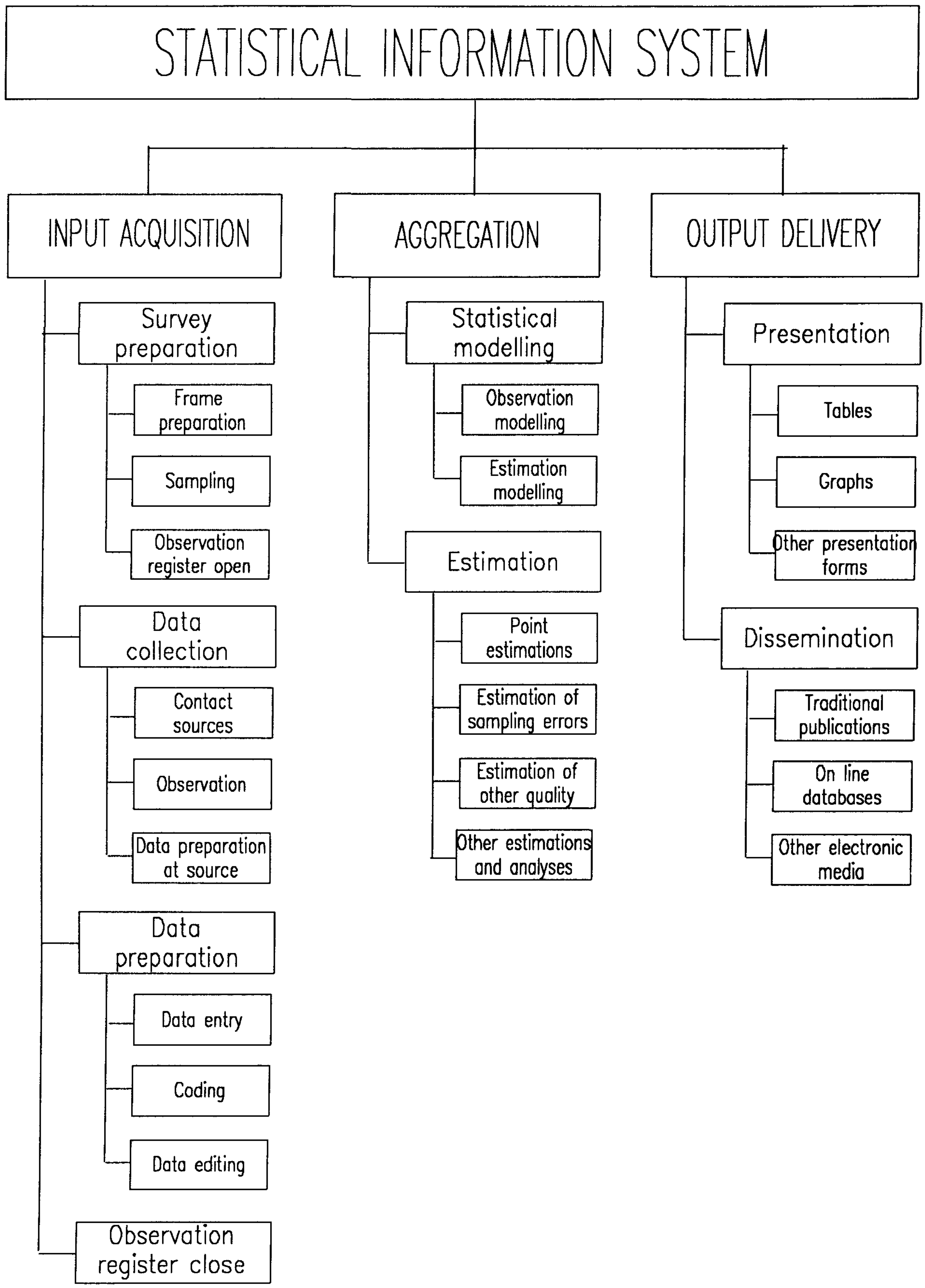



**Figure 3.2.** *A functionally oriented model of a statistical information system.*

# 4 Systems of statistical information systems

## 4.1 Needs for communication and integration in statistical infrastructures

A certain statistical information system typically has needs to interact in different ways with other information systems - statistical as well as non-statistical. For example, the vast majority of input data (more than 95% by volume) to official statistical systems in Sweden are outputs from administrative information systems like taxation registers. Statistical information systems, which fall into the categories of "secondary statistics production" (example: systems of national accounts) and "user-driven retrieval systems" (cf figure 4.1) obtain input data from many other statistical information systems. Moreover, there is a growing international exchange of statistical data.

Figure 4.1 gives an overview of the system of statistical information systems of a statistical office. The individual statistical information systems of such a system of systems belong to some typical categories like

- systems for **primary statistics production** (the traditional type of statistical surveys);
- **instrumental systems** like **registers** consisting of **base registers** and **code registers**;
- systems for **secondary statistics production** like the system of national accounts;
- **retrieval systems** like user-driven **search systems** and **presentation databases**.

Thus there is a need to consider the design of more or less complex systems of statistical information systems - **statistical infrastructures**. Actually a statistical infrastructure of some sort is usually present (explicitly or implicitly) in most organizations. For example, in a company the accounting system is likely to be an important part of the statistical infrastructure. The central statistical office of a country has the specialized task of providing a good statistical infrastructure for a large variety of needs of the citizens, organizations, companies, and rulers of the country. Analogously, international communities have important needs for statistical infrastructures covering many countries.

In particular there is a need to consider communication and integration within and between systems of statistical information systems (and other types of information systems).

Integration of statistical information systems can be accomplished in different ways. The traditional way is **physical integration**, whereby the data and processes of several more or less autonomous statistical information systems are brought together into one physically (and logically) integrated system, which is under the **full centralized control** of one management.

Physical integration of statistical information systems is associated with many problems of physical, logical, and organizational nature. Among other things physical integration will easily lead to a lot of duplication and redundancy, which in turn will cause complex and error-prone update procedures. For example, suppose that there are three (groups of) users, and that each one of the users need statistical information from a subset of a set of 15 different statistical information systems, as illustrated by figure 4.2a. If we create three physically integrated information systems, corresponding to the needs of the three users, respectively, many of the 15 original systems will be duplicated.

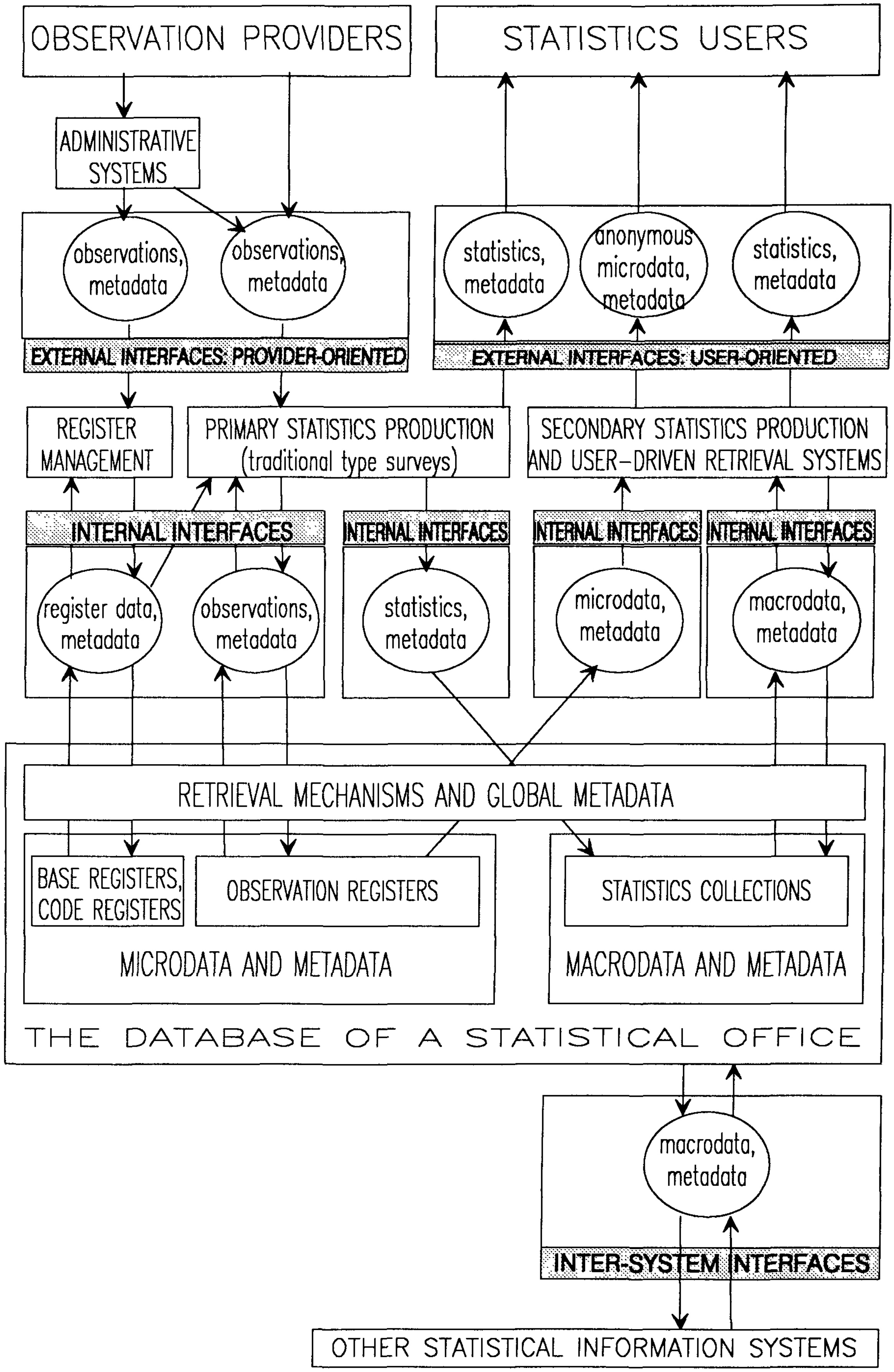



**Figure 4.1.** *The statistical information system of a statistical office.*

An alternative to physical integration is some kind of **soft integration**, where the original information systems remain as autonomous systems, constrained only by some requirements to be able to exchange information between themselves. The communication requirements in such a system of **loosely coupled systems** may be decided upon globally (as the result of dictates or negotiations) or agreed upon after separate negotiations carried out between each user and the manager of each information system from which the respective user is interested to obtain statistical information. In its genuine form the latter model will be very complex and resource-consuming. For example, in a real situation corresponding to figure 4.2a there would have to be 28 different negotiation processes, resulting in 28 individual agreements between a user and the manager of an information system. Johannesson (1993) describes the complexities of "schema integration for heterogenous federated data bases"

Figure 4.2b illustrates a model for soft integration, which avoids the problems of completely decentralized negotiation processes by introducing a very small amount of centralized control in the form of a **standardized interface for exchange of information**: every user and every information system should be able to communicate with the standardized interface, but every user/producer autonomously determines *how* this requirement should be fulfilled. In the terminology of Özsu (1990) our approach is somewhere in between **distributed databases** and **federated databases**. The semantics of the interchange format gives a certain amount of harmonization, without imposing the constraints of a distributed database architecture.

In the situation illustrated by figure 4.2b, there is a need to design (15 + 3) = 18 communication procedures, each one of which can be autonomously decided upon by a single user/producer without any negotiation and with the only restriction that it should be compatible with the standard interface. This should be compared with the situation in figure 4.2a, where there is a need to design 28 communication procedures, each one of which must be negotiated by a user/producer couple.

More generally, if we assume that there are m users and n producers of information, Communication Model 1 (CM1), corresponding to a generalized version of figure 4.2a, will require in the order of (m x n) communication procedures to be designed and bilaterally agreed upon after the same number of negotiations, whereas Communication Model 2 (CM2), corresponding to a generalized version of figure 4.2b, will require in the order of (m + n) communication procedures to be designed and unilaterally decided upon by each user/producer.

Furthermore, if a new user (producer) is added to the scheme, CM1 will require up to n (m) new communication procedures to be designed and bilaterally negotiated, whereas CM2 will require only 1 (1) new communication procedure to be designed and unilaterally decided upon.

Thus systems of statistical information systems (and systems of such systems) can be (more or less) **open** or (more or less) **closed**. A statistical office, controlled by one management, could - at least in theory - design its internal systems for production of statistics as a relatively closed system of physically integrated statistical information systems. Most component systems of such a system will be very dependent on the behaviour of other systems. Thus a change in one system may easily trigger of a chain of (necessary) changes in other systems, and the introduction of a new system into the system of systems will often cause complex integration problems.

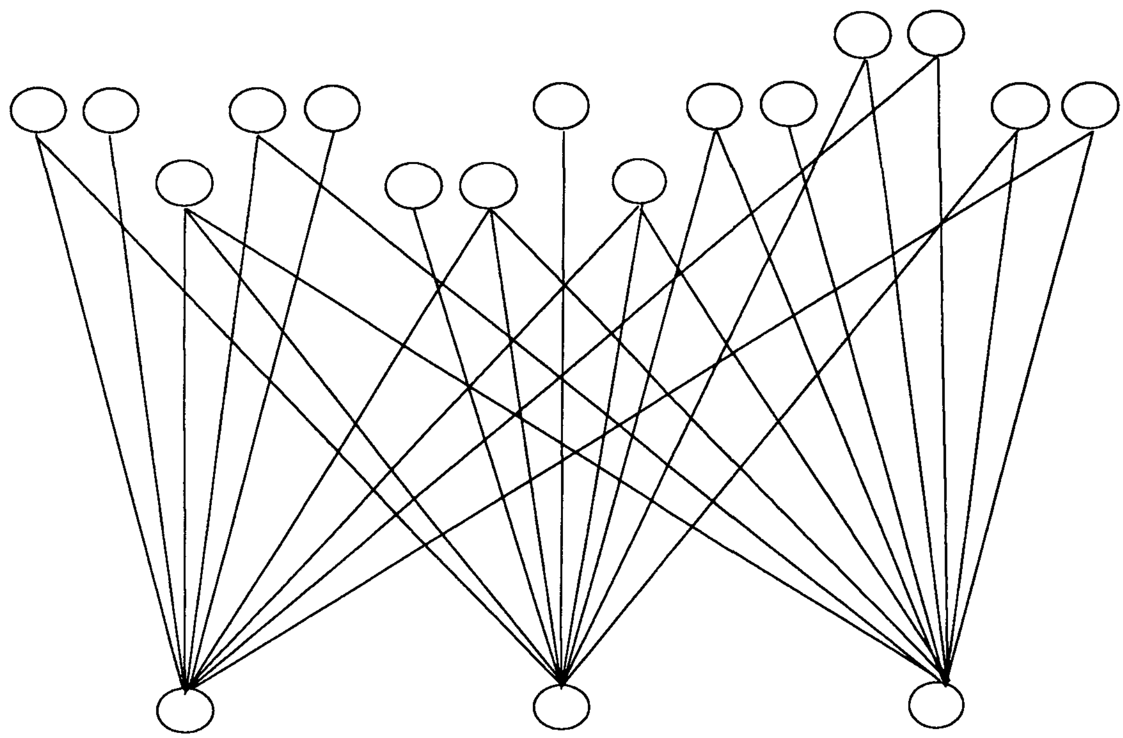


**Figure 4.2a.** *One way of organizing the interaction between two sets of systems.*

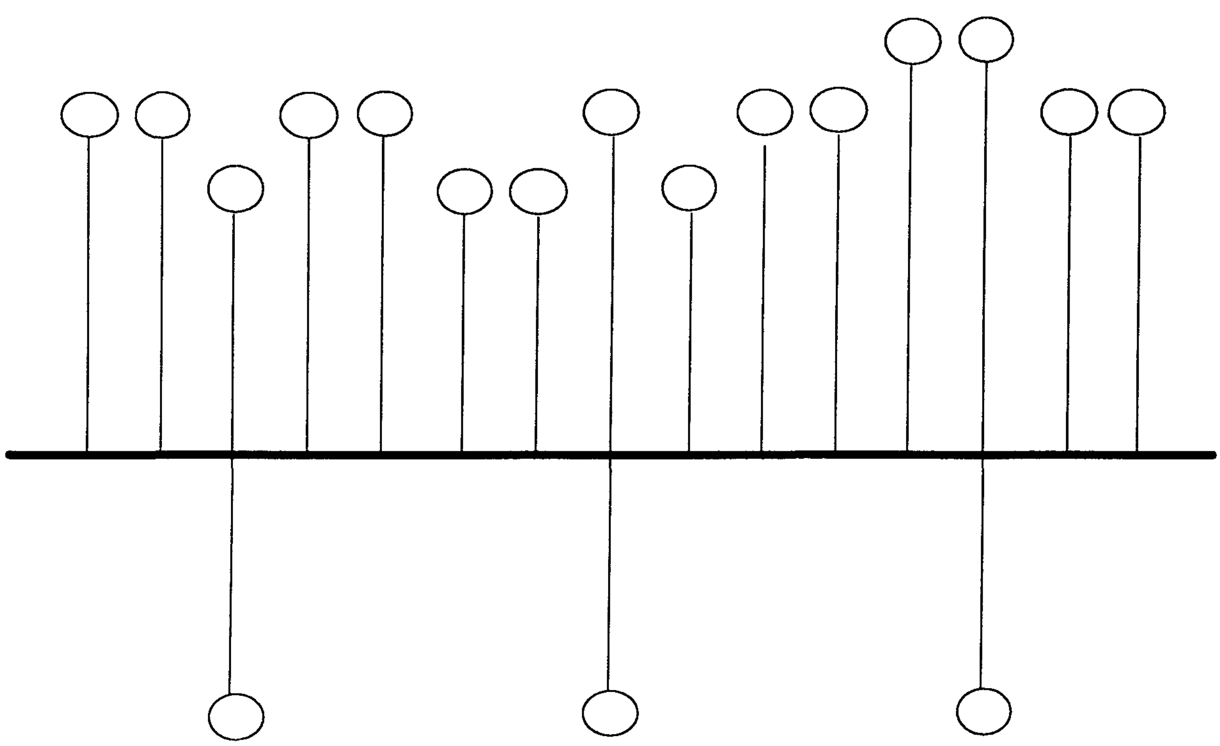


**Figure 4.2b.** *A model for "soft integration" based upon loosely coupled systems communicating via standarized interfaces.*

In a more loosely controlled environment, like an international community of souvereign member states, a closed system of statistical information systems is hardly even theoretically conceivable; an open system of cooperating system is the only practical possibility.

## 4.2 Interface levels

Three major interface levels can be identified within and between statistical information systems (cf figure 4.1):

*Level 1:* Interfaces between a statistical information system (or a system of such systems) and external users/producers of statistical information: **external interfaces**.

*Level 2:* Interfaces between subsystems of statistical information systems: **intra-system interfaces** or **internal interfaces**.

*Level 3:* Interfaces between statistical information systems (or systems of such systems): **inter-system interfaces** or **interfaces between systems**.

### 4.2.1 External interfaces

A statistical information system exchanges information with

(a) **statistics users**;
(b) **input providers** (respondents and/or intermediaries like interviewers or administrative systems).

*Input-oriented external interfaces*

The input providers provide information about **observations and measurements** of a number of object characteristics (states and events) for a number of individual objects in the object system. According to the discussion in section 2 of this paper, an **object characteristic** can be formally represented as an orderd pair

(4.1) $C_O = <O, V>$ or, with dot notation, $C_O = O.V$

where O is an object type and V is a variable. Sometimes O will rather be a vector of object types, in which case V will be a relation or a variable that is based upon a relation, e g "quantity (of a commodity) exported (from one country to another country)".

The basic building-blocks of information about observations and measurements of object characteristics are so-called (micro)object level **elementary messages** (e-messages) with the semantical structure

(4.2) $m_O = <o_i, p, t>$ or, with an alternative notation, $m_O = [o_i.V(t) = v_j]$

where $o_i$ is an object instance belonging to the object type O, p is a property, typically expressed as a value $a_j$ of a variable V, and t is an instance of time (point or interval) at/during which the object is supposed to have (had) the property p. Alternatively $o_i$ could be a vector of objects, p being a relation (like "married") or a $<V, v_j>$ pair, where V is based upon a relation (like in the "export" example above).

In a typical interaction between a statistical information system and an input provider, the latter receives a set of questions, often **hierarchically structured by respondent**. The respondent is sometimes identical with (one of) the object(s) observed. The questions are accompanied by some **metainformation** (explanations, instructions, etc). In some systems additional metainformation may be requested interactively by the respondent, if and when it is needed. When observation messages are returned to the statistical information system, they may be accompanied by other types of metainformation, informing about, say, some exceptional circumstances noted in connection with the observation process.

When the hierarchically structured sets of observation messages enter the statistical information system, they are often - sooner or later - transformed into **flat files** or **relational tables** in accordance with relatively well standardized procedures, supported by many commercial software products (cf form handling tools of relational database management systems). The accompanying metainformation should ideally be systematically taken care of by a parallel process, but this part of the external interface on the input side has not yet reached any degree of standardization.

*Output-oriented external interfaces*

On the output side the external interface traditionally consists of statistical tables accompanied by metainformation in the form of headings, column and row labels, footnotes, comments, etc. Today electronical equivalents of statistical tables are at least equally important, and such outputs are often the result of interactions, which are initiated by a user, and which involve the processing of metadata provided alternately by the user (search questions etc) and by the statistical information system.

The basic building-blocks and typical semantical structures of the aggregated statistical information contained in statistical tables were discussed in section 2. As was noted there, statistics users are often interested to obtain estimated values of "the same" statistical characteristic for

- a series of time periods (rather than a signle one) - "**time series data**"; and/or
- a sturctured set of object populations (rather than a single one) - "**cross-sectional data**".

The GESMES format is a proposed international standard for representation of statistical macroinformation and accompanying metainformation. "GESMES" stands for "Generic Statistical Message", and the standard proposal is developed by the UN/EDIFACT Message Development Group 6.1.

**Observation registers**, containing observed and/or derived microdata, are - beside collections of statistics/macrodata - the other important type of information output from statistical surveys. More and more competent users of statistics demand access to microdata, for their own analyses, in their own computer environments. Statistical offices are responding to such demands by preparing files of **anonymized microdata**, for example so-called **public files**.

An external user who is about to (re)use the microdata in an observation register may not be in a position where he or she has access to the staff in the statistical office, who once (maybe years earlier) produced the data. Thus the observation register will have to be accompanied by an appropriate documentation, that is, a set of metadata.

### 4.2.2 Internal interfaces

Figure 4.3 illustrates the typical structure of one single statistical information system, corresponding to one statistical survey, in a statistical office. A database-oriented architecture is assumed with three major types of subsystems exhanging data and metadata with a common statistical database. The subsystem types are labeled

- input acquisition;
- aggregation;
- output delivery.

In a database-oriented statistical information system most exchange of data takes place via one or more databases. Thus the most important internal interfaces in such systems are the interfaces between the data base management software and the various software products, which are used for performing the basic functions in a statistical information system (cf figure 4.4). Today the most widely accepted, relevant standard for this type of interface is the Structured Query Language (SQL).

It should be noted that SQL does not contain a standard for the exchange of semantically oriented metadata accompanying the data. In the future there may be more complete general (and commercially supported) standards for the exchange of data/metadata between databases and application functions, possibly based upon object-oriented data models rather than relational ones.

### 4.2.3 Inter-system interfaces

As long as we are within a system of statistical information systems, which is - at least in principle - controlled by one single management, this management has certain possibilities to impose standards for internal properties of the interdependent systems and subsystems as well as for interfaces between them. When we consider systems, which - like the statistical system of the European Communities, EC - are not controlled by a single management, imposing standards for internal properties will be virtually impossible, and the necessary negotiation processes for reaching agreements on standards for information exchange between the different member systems. Very open system design principles become a necessity in such situations.

As an example we may consider the model of a proposed Distributed Statistical Information System (DSIS) developed in a study initiated by the Commission of the EC. A key element in this model is the setting up of a European reference environment, which is illustrated on a conceptual level in figure 4.5. Each set of three boxes represents a DSIS organization and the production (P), reference (R), and dissemination (D) environments within those organizations. The shaded portions of the reference environments are those accessible across the DSIS network, and these comprise the European reference environment.

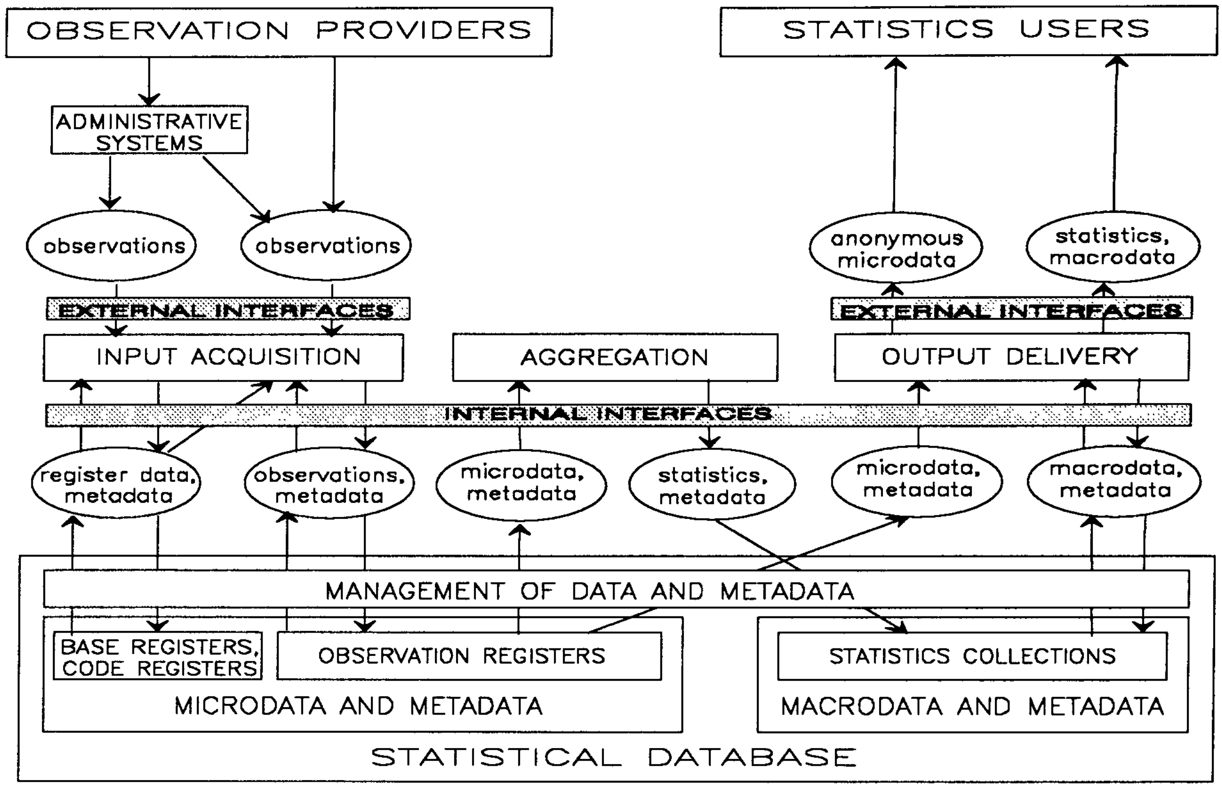



**Figure 4.3.** *A model of a self-describing database-oriented statistical information system.*

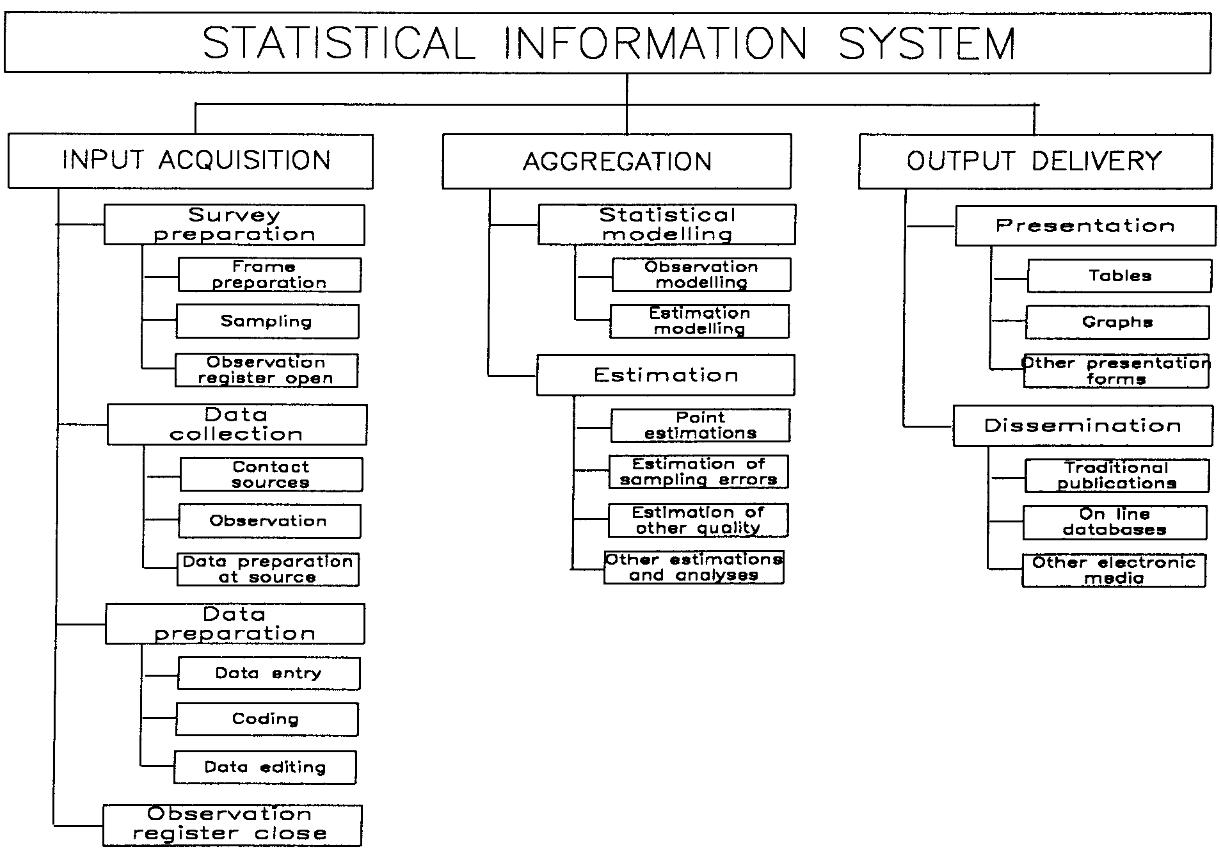



**Figure 4.4.** *A functionally oriented model of a statistical information system.*

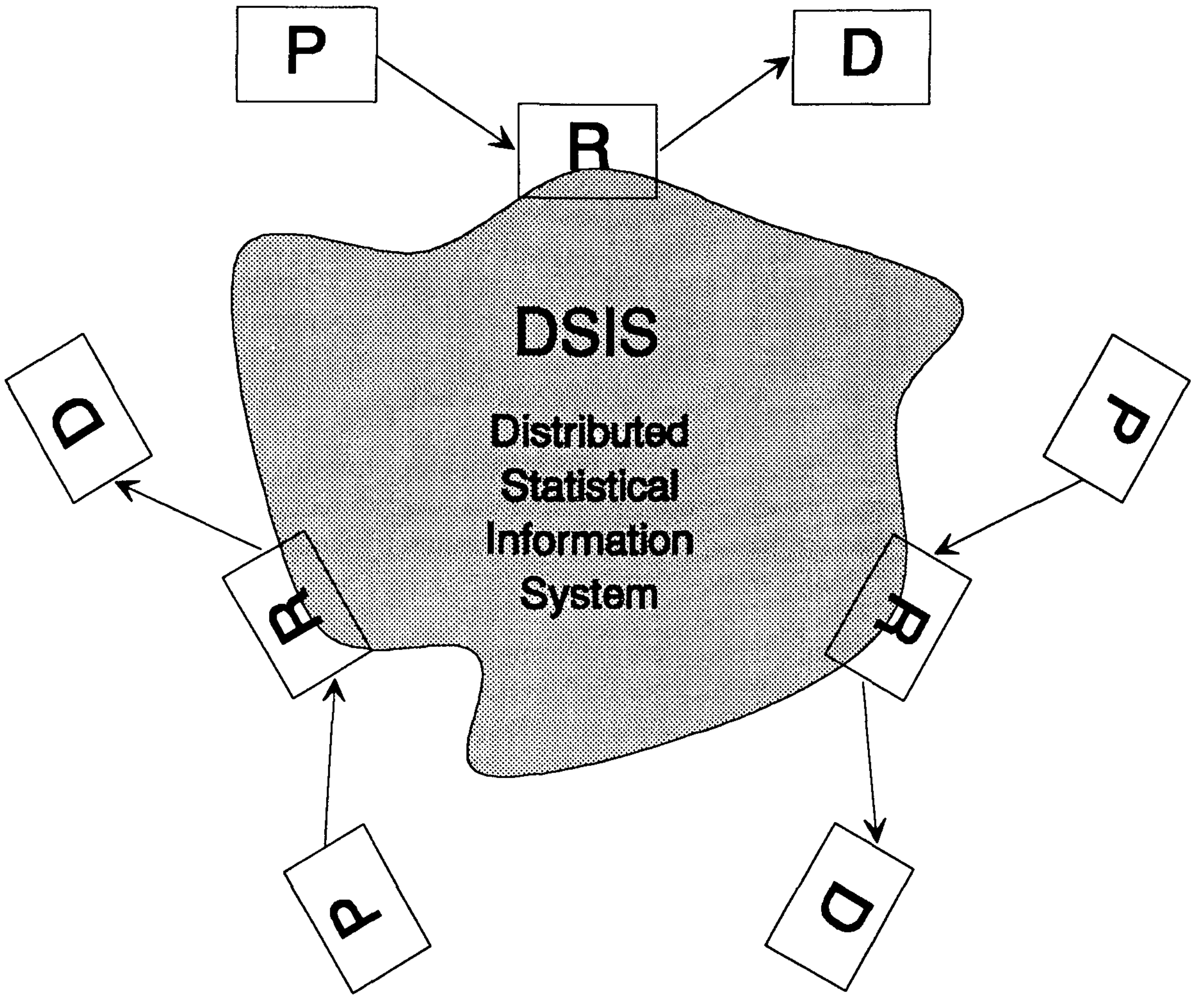



**Figure 4.5.** *A loosely coupled system of statistical information system: the European reference environment.*

# 5 Syntactical properties of statistical information

## 5.1 Input-oriented structures of statistical data: questionnaires and forms

A questionnaire or form for eliciting statistical data from an informant (respondent) has often a hierarchical structure. The root node in the hierarchy corresponds to an object, which is either the respondent or an object that the respondent can inform about. The other non-leaf nodes in the hierarchy usually correspond to objects that are dependent upon the root-node object. The leaf nodes, finally, are the individual questions (or groups of questions) of the questionnaire, and they correspond to variables (or groups of variables) of the objects in the non-leaf nodes.

Like many other types of hierarchical structures, the structure of a questionnaire can be described by means of a **structure diagram**, containing the three structure elements known from structured programming: sequence, selection, and iteration (repetition); see for example Dahl, Dijkstra, and Hoare (1972) and Jackson (1975).

Figure 5.1 illustrates the structure diagram technique applied to an imaginary questionnaire concerning a person's educational background. The diagram should be read as follows. The data collected by the questionnaire consists of four major parts, corresponding to four major sets of questions: first the person is asked for some background information (name, date_of_birth, sex etc), then there are some questions about the basic education that every person is supposed to have, then those people who have undergone some vocational training are asked to supply some information about this, and finally those who have completed one or more programmes of higher education are asked to supply some details about these. Thus there are two mandatory and two optional parts of the questionnaire. A small ring or zero in the upper right part of a box indicates an optional part that will apply once, if it applies at all; an asterisk in the same position indicates an optional part that may be repeated. In this particular questionnaire, the respondent is assumed to have zero or one vocational trainings to inform about, where as the number of higher educations may be zero, one or more. If we look at the details of the main parts of the questionnaire, we can see, for example, that both a basic school education and a higher education programme are supposed to consist of a (variable) number of education component, where each component consists of a subject (course) and an optional judgement (score).

The questionnaire in this example, like many a real-world statistical questionnaire, has a rather complex structure. Nevertheless, it can relatively easily be mapped into the typical flat file structure of a relational database. (As a matter of fact, any state-of-the-art relational database management system would supply a forms-oriented user interface, where the user could define a hierarchical questionnaire like the one in the example, and have the data in it automatically mapped into a specified relational structure.)

One way of designing the mapping between a statistical questionnaire and a relational database is to proceed in the following three steps:

**Step 1.** Model the hierarchical structure of the questionnaire using the diagram technique in figure 5 or some equivalent formalism (for example the PASCAL-based methodology used in the Dutch system BLAISE; see Bethlehem et al (1987).

**Step 2.** Develop the OPR-model underlying the questionnaire, unless it already exists; it is always possible to find a conceptual OPR-model, which will make it possible to define the hierarchical questionnaire structure as a **view**, or **external schema**, in database terminology.

**Step 3.** Transform the OPR-model into a relational data model. This can always be done by applying some simple transformation rules; See Sundgren (1984) and Elmasri and Navathe (1989).

Figure 5.1 illustrated the result of step 1 for a simple example. Figures 5.2 and 5.3 illustrate the results of step 2 and 3 for the same example.

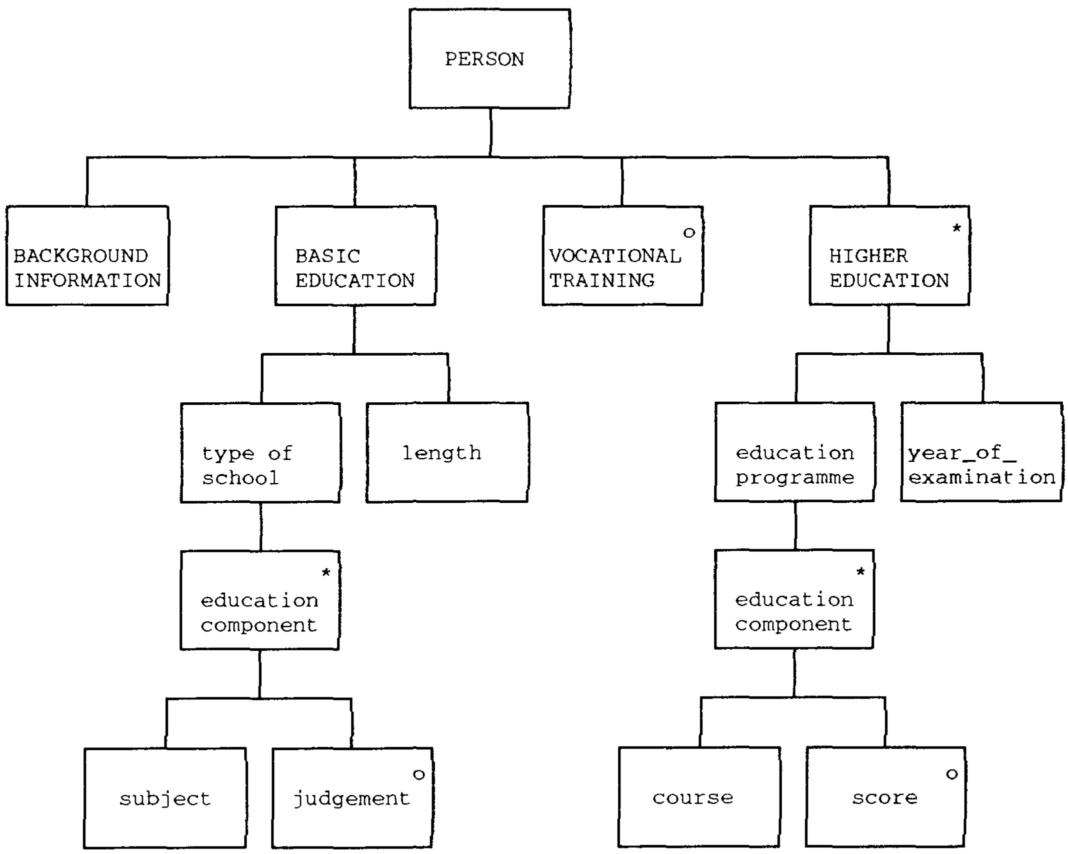



**Figure 5.1.** *Structure diagram illustrating the typical, hierarchical structure of a statistical questionnaire.* (The diagram technique follows Jackson (1975), but some conventions have been adopted, which make the diagram more compact.)

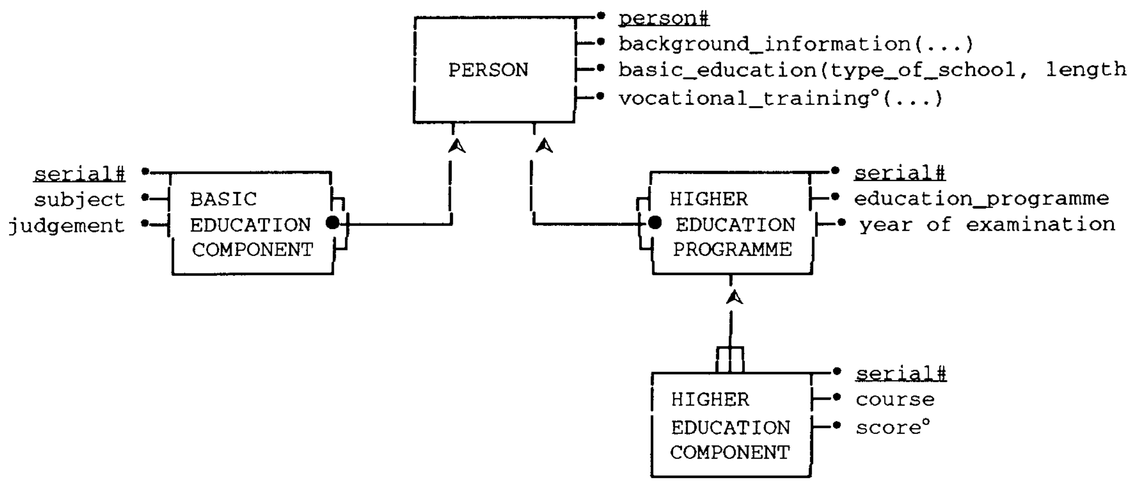



**Figure 5.2.** *An object graph showing the OPR-model underlying the hierarchical structure of the statistical questionnaire in figur 5.*

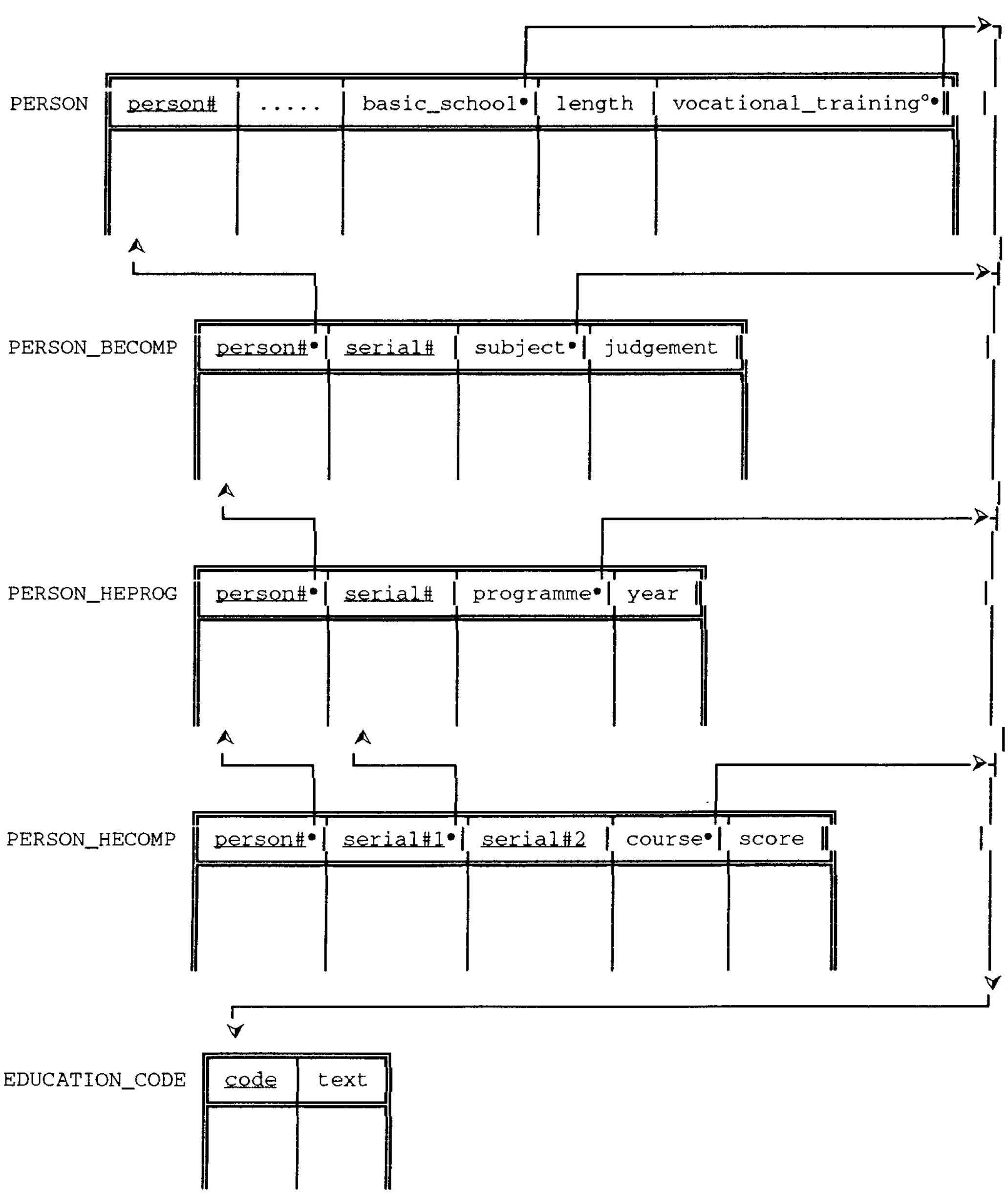


**Figure 5.3.** *A relational data model corresponding to the conceptual OPR-model in figure 6 and the questionnaire in figure 5.1.*

## 5.2 Output-oriented structures of statistical data: statistical tables

There are several techniques, known from the literature, for describing the semantical and syntactical structure of statistical tables; see for example Shoshani (1982) and Sato (1988). One problem is to which extent semantical and syntactical aspects of the table structure should be treated separately, and to which extent they should be mixed together. From a purely syntactical point of view, the most fundamental structure is the two dimensions of the paper or screen upon which the table is usually presented. On the other hand, from a purely semantical point of view, the basic structure is determined by (a) the principal logical parts of the definition of the information contents of a table, and (b) the components of each one of these logical parts.

In my opinion it is unnecessarily complex to describe and understand the syntactical structure of a statistical table, without having first a good semantical analysis of the table.

A statistical table is a structured representation of a structured set of statistical messages. Let us consider a cell in a typical statistical table. It usually contains a number, and it is further characterized by its place in the table structure, together with the textual information associated with this place (head and stub texts etc). The data and the associated metadata of a cell in a table represents a piece of statistical information that we can call a **statistical e-message**.

The object part of a statistical e-message refers an object group, which is a population of objects of interest, or a subset of such a population, a so-called domain of interest, or domain of study. The object group is a macro-object resulting from an abstraction by aggregation. Thus the macro-level object can be defined in terms of a micro-level object type and a property giving a restriction to a subtype:

<object type> **with** <property>;

Example:

PERSON **with** sex="female" **and** age<20;

The property part of a statistical e-message typically refers to a <variable, value>-pair, where the variable is a so-called parameter or characteristic of the domain of interest referred to by the object part of the message, and where the value is the value referred to by the number in the table cell. Example:

estimated_average_income = 15000;

The time part of a statistical e-message can be a point of time (if the e-message informs about a state in the domain of interest) or a time interval (if the e-message informs about a change in the domain of interest. The time part is often the same for all the statistical e-messages in a table, and then it can be mentioned in the table head only. However, if the table contains statistical information that is organized as one or more time series, common time parts for subcollections of e-messages (cells) may appear in column heads or in the stub.

Thus an example of a complete statistical e-message could be:

<PERSON **with** sex="f" **and** age<20, est_avg_income=15000, year=1990>;

In the syntax of INFOL this could be expressed as:

{PERSON(**with** sex="f" **and** age<20)}.est_avg_income(year=1990)=15000;

In the introduction to this section we defined a statistical table as a structured representation of a structured set of statistical messages. Many tables appearing in statistical presentations have a very regular structure, at least from a semantical point of view. In fact it could be argued that even tables, which are not quite so regular, could and should be thought of as being built up from components that are regular. The regular structure that we are now going to discuss has been referred to in the literature as the **box structure** or **matrix format** of statistical tables.

A **box** is an n-dimensional structure defined or "spanned" by n variables, called $\gamma$-variables. The Cartesian product of the value sets of the n $\gamma$-variables defines the **cells** of the box. Each cell contains a vector of m values of m variables, called $\beta$-variables. The $\beta$-variables are the same for all cells in a box, and they are supposed to be statistics or estimated parameters for domains of interest corresponding to the respective cells. The domain of interest associated with a particular cell is defined by (a) the population property, sometimes called the $\alpha$-property, which is the same for all the domains of interest corresponding to all the cells in the box, and (b) the property distinguishing the particular domain of interest, associated with the particular cell, from the domains of interest of the other cells in the box; the latter property is called the $\gamma$-property, since it is defined by a logical **and**-combination of n <$\gamma$-variable, value>-pairs:

$P_\gamma = (\gamma_1 = v_1)$ **and** $(\gamma_2 = v_2)$ **and** ... **and** $(\gamma_n = v_n)$

For example, the information defined by the INFOL-expression

{PERSON(**with** nationality="foreign")(**by** sex $\times$ region)}.est_avg_income(1990)

can be organized as a two-dimensional box spanned by the $\gamma$-variables "sex" and "region". Each cell would contain a value of the $\beta$-variable "est_avg_income(1990)" for a domain of interest defined by the $\alpha$-property "PERSON(**with** nationality= "foreign")" **and** a $\gamma$-property defined by a certain <sex value, region value> combination.

In terms of the relational data model, a box can always be represented by a relational table, having a column combination corresponding to the n $\gamma$-variables as its primary key, and columns corresponding to the m $\beta$-variables as additional columns. In the example above, we would get the following relational table, if we assume that "region" has three values: A, B, and C;

FOREIGNERS =

| SEX | REGION | EST_AVG_INCOME(1990) |
|---|---|---|
| female | A | ..... |
| female | B | ..... |
| female | C | ..... |
| male | A | ..... |
| male | B | ..... |
| male | C | ..... |

This mapping of a box structure to a relational table could be regarded as a **normal representation** of statistical tables. Naturally, in many situations one like a representation for presentation purposes, which looks quite different from this normal representation, but with contemporary computer technology and software tools, it should not be difficult for a user to transform a table, stored according to the normal representation, into his or her preferred format in a particular usage situation. On the other hand, for facilitating automatic exchange of statistical data and metadata, it would be extremely valuable if a standard representation format, like the above-mentioned UN/EDIFACT GESMES, could be agreed upon.

Of course the example used above for illustration purposes is extremely simplified. There are many qualifications that need to be added. Consider the following list of problem areas:

- sums on different levels;
- hierarchical variables;
- sparse tables;
- null values;
- time;

Derivable data like sums can be represented explicitly or implicitly. Implicit representation means that we indicate in our metadata description of a table that we want the sums to be computed, whenever the table is presented to the user. (Naturally different users, and even the same user, can have different definitions of the same table for different purposes.) Explicit representation of derivable data implies redundance but may speed up retrieval. Generally speaking, redundance means additional storage costs and updating problems; however the updating problems need not be too severe in statistical databases, since they are often quite statical by nature, and updated incrementally only.

In a specification and query language like INFOL, we may indicate by a suitable symbolism, which total and partial sums that we would like to specify. Example:

{FOREIGNER(**by** sex(*, $\Sigma$(*)) $\times$ region(A, B, $\Sigma$(A, B), C, $\Sigma$(*))}. est_avg_income(1990)

First of all, we have here introduced the name "FOREIGNER" to mean the same as "PERSON(**with** nationality="foreign")". Then we have indicated, variable by variable, which values and (total and partial) sums that we want to be available for a particular usage of aggregated data. For example, an asterisk (*) indicates the selection of all values in the value set for a particular variable, and $\Sigma$(...) indicates that the $\beta$-variables should be aggregated over the listed values of the $\gamma$-variable (according to the proper formula for each variable, depending on whether it is a total, an average, a percentage, or whatever).

The normal form representation of this selection would be:

FOREIGNERS =

| SEX | REGION | EST_AVG_INCOME(1990) |
|---|---|---|
| female | A | ..... |
| female | B | ..... |
| female | A, B | ..... |
| female | C | ..... |
| female | * | ..... |
| male | A | ..... |
| male | B | ..... |
| male | A, B | ..... |
| male | C | ..... |
| male | * | ..... |
| * | A | ..... |
| * | B | ..... |
| * | A, B | ..... |
| * | C | ..... |
| * | * | ..... |

As can be seen from this example, the introduction of a summary level for a $\gamma$-variable is equivalent to extending the value set with one element. With one summary level introduced for "sex" and two for "region", the cardinalities of the value sets will grow from 2 to 3, and from 3 to 5, respectively, and the number of rows in the relational table will grow from $2 \times 3 = 6$ to $(2 + 1) \times (3 + 2) = 15$, that is, by 150% in this case.

Null values can be treated in much the same way as summary values.

One or more of the $\gamma$-variables can be **hierarchical variable**. A hierarchical variable of k levels will be represented by k columns in the normal format relational table. For each level in the hierarchy, one or more summary values may be introduced. However, the summary values for different levels in the hierarchy cannot be chosen as independently of each other as they can for the variables in a crossclassification.

As an example, we may assume that "region" in the example above is a two level hierarchy "county:municipality", where county A consists of the municipalities A1 and A2, county B consists of the only municipality B1, and county C consists of the municipalities C1, C2, and C3. The information specified by the INFOL expression

{FOREIGNER(**by** sex(*) $\times$ county(*, $\Sigma$(*)) : municipality(*, $\Sigma$(*))}. est_avg_income(1990)

would have the normal form representation (only the first part of it is shown):

FOREIGNER =

| SEX | COUNTY | MPLTY | EST_AVG_INCOME (1990) |
|---|---|---|---|
| fem | A | 1 | ..... |
| fem | A | 2 | ..... |
| fem | A | * | ..... |
| fem | B | 1 | ..... |
| fem | B | * | ..... |
| fem | C | 1 | ..... |
| fem | C | 2 | ..... |
| fem | C | 3 | ..... |
| fem | C | * | ..... |
| fem | * | * | ..... |

So far we have assumed without discussion that the time component of the statistical table should be associated with the β-variable(s) and the column(s) representing the β-variables. However, there are several alternatives, corresponding to slightly different semantical interpretations of the data, and with different performance characteristics, if implemented in a relational database.

If the table is a typical snapshot representation of the object system, there is only one time involved, and this time could be indicated in the metadata accompanying the table as a whole. In the example above, the relational table could for example be named "FOREIGNER(1990)".

If there are repeated snapshots, there could be uniform tables for different times, with names containing a time parameter. Example: "FOREIGNER(t)", where t = 1980, 1985, 1990. Another alternative is to put time as a parameter in the names of the β-variables. Example: "est_avg_income(t)", where t = 1980, 1985, 1990.

A third alternative is to regard time as a γ-variable, which is crossclassified with the other γ-variables. This implies a slight change in our conceptualization of the population of interest. If the "snapshot version" of our population of interest is assumed to contain objects of a certain type OBJ, a corresponding population with extension in time would constist of <OBJ, time> pairs, and interest groups would be formed by crossclassifying this population by means of the Cartesian product of the original γ-variables with an additional γ-variable that is based on time.

*Example:*

{<PERSON, TIME>
(**with** PERSON.nationality="foreign" **and** TIME.year = 1985 **or** 1990)
(**by** PERSON.sex × PERSON.region × TIME.year)}. est_avg_income;

The normal relational representation of this conceptualization would be:

FOREIGNERS =

| SEX | REGION | TIME | EST_AVG_INCOME |
|---|---|---|---|
| female | A | 1985 | ..... |
| female | A | 1990 | ..... |
| female | B | 1985 | ..... |
| female | B | 1990 | ..... |
| female | C | 1985 | ..... |
| female | C | 1990 | ..... |
| male | A | 1985 | ..... |
| male | A | 1990 | ..... |
| male | B | 1985 | ..... |
| male | B | 1990 | ..... |
| male | C | 1985 | ..... |
| male | C | 1990 | ..... |

Summary values can be defined as in previous examples. However, it should be noted that the meaning of summary values formed over the time γ-variable may not be obvious. In fact it would very often not be meaningful at all.

Yet another modelling of time will be necessary for **event-based statistical information.** In contrast to the snapshot-based statistical information that typically emanates from a statistical survey of traditional type, event-based statistical information often comes from other than statistical sources, for example administrative registers and other administrative information systems. Such systems are more or less directly updated, when events of certain types occur in the object system. The flow of such events (and consequent updates) is more or less continuous, and the updating transactions must be **time-stamped.** As a matter of fact the events will be a basic object type, forming at least one of the populations of interest, in the conceptual model for this type of statistical information. The time of the event will be a variable of the event object, and if the value set of the time variable is properly classified (grouped), it can serve as a γ-variable very much like other γ-variables in the aggregation and tabular presentation of statistical information. For this type of time γ-variable, the formation of summary values is usually meaningful and often useful, since it is meaningful to count events over different periods of time, and to summarize other variables for these events.

Apart from events, **processes** is another type of object, which sometimes occur in event-based statistical systems. A process is characterized in the time dimension by a starting-point (associated with a process birth event) and a completion-point (associated with a process death event). Processes can be treated similarly as events in the aggregation of statistical information.

So far we have discussed the semantical structure of statistical macroinformation, and how it can be represented by relational tables in a kind of canonical form for statistical macrodata. However, we still have to discuss desirable presentation structures for statistical macrodata, as well as operators needed to transform the statistical macrodata from the normal representation form to other desirable formats. In this paper I shall only give a few hints about these topics.

The most straightforward presentation of a box structure of statistical data that is stored in its normal relational form is a listing of the relational table, row by row. Such a presentation would not be satisfactory in many situations, even if one made some cosmetical improvements, such as suppressing γ-variable values whenever they are identical with the corresponding values in the previous row. A transformation of a slightly more complicated nature, which is often desirable, is to move one or more of the γ-variables from the stub of the table to the column heads. Example:

| County | Municipality | Estimated average income 1990 | | |
|---|---|---|---|---|
| | | Men | Women | Both sexes |
| A | | ..... | ..... | ..... |
| | 1 | ..... | ..... | ..... |
| | 2 | ..... | ..... | ..... |
| B | | ..... | ..... | ..... |
| | 1 | ..... | ..... | ..... |
| C | | ..... | ..... | ..... |
| | 1 | ..... | ..... | ..... |
| | 2 | ..... | ..... | ..... |
| | 3 | ..... | ..... | ..... |
| All counties | | ..... | ..... | ..... |

The moving of the γ-variable "sex" from the stub to the column headings in this example can be done by operations in an extended relational algebra. However, it is a relatively complex operation, and it implies a non-uniform handling of the value names for γ-variables in the stub and γ-variables in the column headings; the former are normal data in the relational table, whereas the latter must be part of the column names.

A much more attractive solution to this problem (and similar ones) is to define a **box algebra**, that is, an algebra the operators of which transform boxes into boxes of another structure. Such algebras have been proposed and implemented; see for example Nilsson (1984).

Another type of problem arises when the user wants to have the aggregated statistical data presented in a non-regular form, that is, a form which is not compatible with the box structure as such. Usually, however, such non-regular presentation structures can be constructed from a small number of regular boxes. A relatively common situation is when the user wants to present in the same table the contents of two boxes that have all γ-variables except one (more general: k) in common. Example:

| County | Munici-pality | Estimated average income 1990 | | | | |
|---|---|---|---|---|---|---|
| | | By sex | | By marital status | | |
| | | Male | Female | Never married | Married now | Married before |
| A | | ..... | ..... | ..... | ..... | ..... |
| | 1 | ..... | ..... | ..... | ..... | ..... |
| | 2 | ..... | ..... | ..... | ..... | ..... |
| B | | ..... | ..... | ..... | ..... | ..... |
| | 1 | ..... | ..... | ..... | ..... | ..... |
| C | | ..... | ..... | ..... | ..... | ..... |
| | 1 | ..... | ..... | ..... | ..... | ..... |
| | 2 | ..... | ..... | ..... | ..... | ..... |
| | 3 | ..... | ..... | ..... | ..... | ..... |
| All | | ..... | ..... | ..... | ..... | ..... |

## 6 Appendix: A formal specification of the INFOL language

### 6.1 The metalanguage of the formal specification

[...] The brackets embrace something that may be omitted.

[...]* The construction within the brackets may be repeated a variable number of times (zero, one or more), with a comma between the repetitions; in other words the whole construction is a list (an ordered set) of constructions of the same kind.

<...> Indicates that at this place in a construction there should be an element of the type mentioned within the broken brackets.

... <--- ... The structure of an INFOL definition. The construction to the left of the arrow is what is defined by the definition. The construction to the right of the arrow is the construction which defines the construction to the left.

... ::= ...; The structure of a metalanguage definition.

| Denotes logical "or" in metalanguage definitions, that is, indicates alternative construction possibilities.

obj object

prop property

rel relation

var variable

val value

ref reference

relop relational operator (<, =, >, etc)

### 6.2 INFOL constructions

(1) <obj type ref> ::= <obj type name> |<br><obj type ref> [**with** <prop ref>] |<br><obj type ref> [**by** <var ref>].**agg**;

(2) <prop ref> ::= <prop name> |<br><var ref> <relop> <var ref> |<br>**not** <prop ref> |<br><prop ref> **and** <prop ref> |<br><prop ref> **or** <prop ref>;

(3) <var ref> ::= <var name> |<br><path ref>.<var ref> |

<function>([<var ref>]*) |
<quantifier> <var ref>;

(4) <val set ref> ::= <val set name> |
<function>([<val set ref>]*);

(5) <val ref> ::= <val name> |
<val set ref>.<val name>;

(6) <function> ::= <arithmetical function> |
<string function> |
<set function> |
<logical function> |
<aggregation function>;

(7) <path ref> ::= [<rel ref>.[<quantifier>] <obj type ref>]*;

(8) <quantifier> ::= **some** | **all**;

(9) <rel ref> ::= <rel name> |
[<path ref>]*;

(10) <definition> ::= **object type** <obj type name> [**with variables**]
[.[<var name>[(<val set name>)]]*]
[<--- <obj type ref>][.[<var ref>]*]] |
**property** <prop name> [<--- <prop ref>] |
**variable** [<obj type ref>.]
<var name>[(<val set name>)]
[<--- [<var ref>[, **if** <prop ref>]]*] |
**value set** <val set name> **with values**
[<val name>]* |
**value set** <val set name>(<val set name>)
<--- [<val name>, **if** [<val name>]*]* |
**value** [<val set name>.]<val name>
[<--- <val ref>] |
**relation** <rel name> **between objects**
[<obj type name>(<cardinality>)
[**alias** <role name>]]*
[<--- <rel ref>];

(11) <query> ::= <obj type ref>.[<var ref>]*;

(12) <view> ::= <obj type ref>.[<var ref>]* |
[**object type** <obj type name> [**with variables**]
.[<var name>]*]*,
[**relation** <rel name>]*;

## 6.3 Informal comments, qualifications, and explanations

First a general comment. The first object type referred to in an INFOL expressions will be the first **current object type** when the expression is processed (by a human being or otherwize).

The current object type will be changed as a result of certain constructions that appear in INFOL expression. For example, a path reference will "move" the current object type from one object type to another, via still other object types, which are "nodes" on the path. The properties, variables, and relations, referred to at a certain place in an INFOL expression, must be *compatible with the current object type* at that place. For example, if a variable is referred to, it must be relevant for the current object type at the place of the variable reference. Now will follow a numbered sequence of further comments related to the formal definitions with the corresponding numbers in the previous section:

(1) A practical convention is to let the object aggregation operator **agg** be implied, if it is followed by a variable reference that starts with an aggregation function like **count**, **sum**, or **avg**. Another possibility, which has been illustrated in the paper, is to use set brackets {...} around the classification expression, instead of writing **agg** after it.

(2) Note that <var ref> includes a reference to a constant value as a special case; a constant value can be regardes as a special case of a function.

(6) The arithmetical functions are the usual ones. String functions include concatenation and substring operations. Set functions include Cartesian product (×) and hierarchical combination (:). Aggregation functions include functions that operate on the values of zero, one, or more variables for a *set of object instances* and produce a single value as an outcome. In addition to the functions mentioned above, and a other statistical operators like those which compute variance and correlation, there are functions like **max** and **min**.

(7) Intuitively speaking, a path connects two object type nodes in an object graph. The connection consists of a chain of segments, where the start node and the end node of every segment are object types that are *directly related* in the object graph. If there is only one direct relation between two nodes, a practical convention may be to omit the relation reference in the path description. Alternatively, it is always possible to omit a reference to an object type at the end of a segment corresponding to a binary relation, since the object type is uniquely determined anyhow.

(8) The quantifiers **some** and **all** correspond to the *existence quantifier* (∃) and the *universal quantifier* (∀) known from predicate logic.

(10) The definition of an INFOL entity consists in general of two parts. The first part is a **declaration**, which (a) declares the new entity to belong to a specified category (for example "object type"), and (b) gives a name to the entity. The second part of the definition is separated from the first one by an arrow (<---), and it contains a **derivation expression**, that is, an expression for deriving the new entity from existing ones. Of course, the second part appears only if the new entity is derivable. If the first part of the definition is missing, it is an **implicit definition**; the category of an implicitly defined entity is implied by the context, and the name, if needed, will have to be automatically generated.

(11) This seemingly simple expression actually covers the whole query language of INFOL, including so-called αβ-queries and αβγ-queries (see Sundgren (1973)), and it can be regarded as a conceptual level counterpart to database query languages like SQL.

(12) The first type of view definition creates a **single-object view**, that is, a view which arranges all information around one single object. The other type of view definition creates a **multi-object view**, containing several object types and relations. The single-object view is often useful as a basis for statistical tabulations.

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