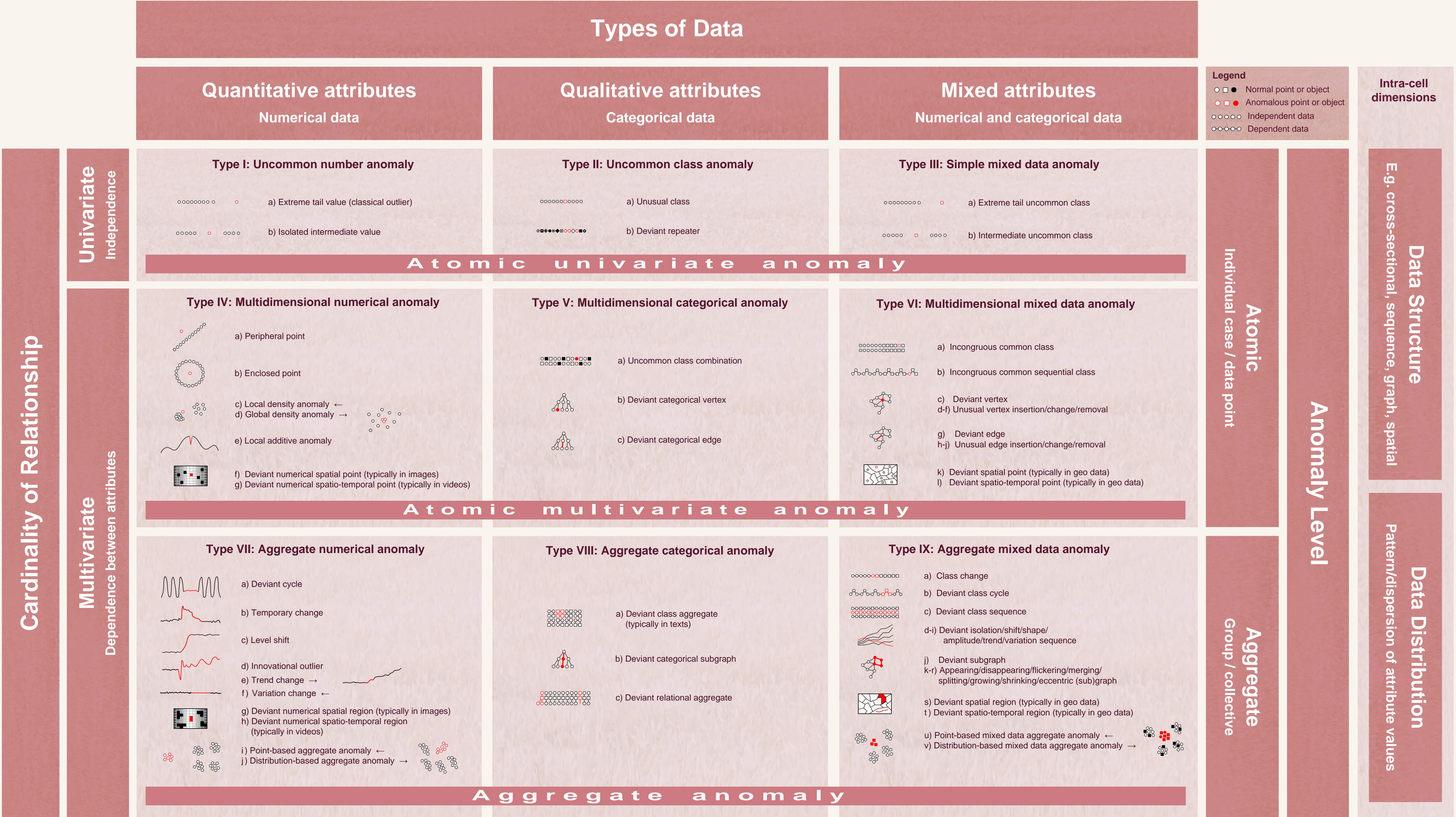


Typology of Outliers and Other Anomalies

A full overview of the kinds of anomalies that can be encountered in datasets. For a detailed explanation of all groups, types and subtypes, download the free open access publication: Foorthuis, R.M. (2021). *On the Nature and Types of Anomalies: A Review of Deviations in Data*. International Journal of Data Science and Analytics, Vol. 12, No. 4.



The typology of anomalies presents a full overview of the kinds of anomalies that can be encountered in datasets. Detecting anomalies can help with increasing the quality of your data, or with identifying risks, errors, opportunities and other interesting phenomena. The typology describes 3 broad groups, 9 basic types, and 63 concrete subtypes of anomalies.

The typology’s rows represent **3 broad groups** of anomalies

Each of the broad groups has three basic types of anomalies, resulting in a total of **9 basic types**

Atomic univariate anomalies are single cases with a deviant value for an individual attribute (possibly multiple attributes, but each individual value is deviant in its own right). They are relatively easy to describe and detect because the individual values are unusual, and relationships between attributes or cases are not relevant.

I. Uncommon number anomaly: This is a case with an extremely high, low or otherwise unusual value for a single quantitative attribute (or multiple, but these are then anomalies in their own right). These deviant numbers often manifest themselves as an *extreme tail value* (ST-Ia), i.e. an unusually high or low number. An example is an unrealistically high numerical value, such as a person reported to be 269 cm high. However, it can also be located in the middle of the value range, thus an *isolated intermediate value* (ST-Ib) in between the majority of the data.

II. Uncommon class anomaly: This can manifest itself as an *unusual class* (ST-IIa), i.e. a case with a unique or rare categorical value for a single qualitative variable (or for multiple, but these are then anomalies in their own right). For example, the label ‘monkey’ will be unusual if all other labels represent insects and birds. Alternatively, it can be a *deviant repeater* (ST-IIb), i.e. a frequently occurring value in a set in which most values are unique, such in a collection of identifying codes.

III. Simple mixed data anomaly: This is a case that is both a Type I and a Type II anomaly, i.e. with at least one isolated numerical value and one uncommon class. An example is a data point with a unique class label that lies at an isolated intermediate location in the numerical space, a so-called *intermediate uncommon class* (ST-IIIb). However, like Type I and II anomalies, analyzing the attributes jointly is not necessary because the case in question is not multivariately anomalous. This type involves a set of individually deviant attribute values.

Atomic multivariate anomalies are single cases whose deviant nature lies in their relationships, with the individual values not being anomalous. In independent data this will manifest itself in the unusual combination of a case’s own attribute values, such as a 10 year old person with a body length of 180 cm. However, the multivariate nature also allows defining and detecting deviations in dependent data, i.e. in the relation with the other cases to which the given case is linked. An example is a time series temperature measurement that is unusually high for winter, but that would have been normal in summer.

IV. Multidimensional numerical anomaly: This is a case that does not fit the general patterns when the relationship between multiple quantitative attributes is taken into account, without showing unusual values for any of the individual attributes that partake in this relationship. The so-called *peripheral point* (ST-IVa) is an isolated datapoint that lies outside the dense multivariate cluster. An example is a person who is 182 cm tall and weighs 53 kilos, i.e. an unusual combination of normal individual values. A Type IV anomaly can also reside in dependent data such as time series. For example, the *local additive anomaly* (ST-IVe) is a short-lived spike that deviates from the local temporal neighborhood – e.g. the current season or trend – without exhibiting globally extreme values. Other Type IV anomalies can lie in spatial data.

V. Multidimensional categorical anomaly: This is a case that does not fit the general patterns when the relationship between multiple qualitative attributes is taken into account, without showing unusual values for any of the individual attributes that partake in this relationship. In short, a case with a rare or unique combination of class values. A subtype in independent data is the *uncommon class combination* (ST-Va), such as this curious combination of values from three attributes used to describe dogs: ‘MALE’, ‘PUPPY’ and ‘PREGNANT’. A subtype in dependent data is the *deviant categorical vertex* (ST-Vb), which is an uncommon node in a tree or other form of graph data structure. An example is a node with a label that is different from the labels of the nodes it is connected to.

VI. Multidimensional mixed data anomaly: This is a case that does not fit the general patterns when the relationship between multiple quantitative and qualitative attributes is taken into account, without being an atomic univariate anomaly with regard to any of the individual attributes that partake in this relationship. It concerns a case with an unusual combination of qualitative and quantitative attributes. In a set with independent data the anomalous case generally has a class value (or combination thereof) that in itself is not rare in the dataset from a global perspective, but is only uncommon in its own neighborhood. Such cases thus seem to be mislabeled or misplaced. The *incongruous common class* (ST-VIa) is such an anomaly. In dependent data a Type VI anomaly can manifest itself in many other ways. An *incongruous common sequential class* (ST-VIb), for example, is an individual deviant in a sequence of class values that show a sequential pattern to which the anomaly does not conform. Other subtypes may lie in complex graph data structures or spatial datasets.

Aggregate anomalies are groups of cases that deviate as a collective, of which the constituent cases usually are not individually anomalous. Relationships between attributes and between cases not only position an occurrence in the set with dependent data, but also form a pre-defined or derived group. Owing to their complex and intricate nature, these anomalies are generally the most difficult to describe and detect. A deviant subsequence is one manifestation of an aggregate anomaly, such as a whole winter with many unusually high temperatures compared to other winters.

VII. Aggregate numerical anomaly: This is a group of related cases that deviate as a collective with regard to their quantitative attributes. Such anomaly subtypes are often found in time series data, in which they constitute a subsequence of the entire sequence. For example, the *deviant cycle* (ST-VIIa) occurs when the respective cycle (e.g. a season) follows a different pattern than the other cycles. The *temporary change* (ST-VIIb) is a rise or fall of the substantive value that requires a certain period to get back to the regular level. The *level shift* (ST-VIIc) is an abrupt structural change to a higher or lower value level. Type VII anomalies can also be found in spatial data. Independent datasets can host them as well, such as the *distribution-based aggregate anomaly* (ST-VIIj), which is a whole cluster with unusual characteristics at the collective level, such as a group of data points with a different orientation, (co)variance, mean or frequency.

VIII. Aggregate categorical anomaly: This is a group of related cases that deviate as a collective with regard to their qualitative attributes. A *deviant class aggregate* (ST-VIIIa) often manifests itself as a deviant text paragraph, section or document. The aggregate is for example a bag-of-words or a collection of sentences that stands out in terms of topic, style or tone. A *deviant relational aggregate* (ST-VIIIc) is a collective anomaly as a result of its relationships. Such complex aggregates are usually comprised of several domain-specific entities that are inter-related by one-to-many relationships, and are typically stored in different tables in a relational database.

IX. Aggregate mixed data anomaly: This is a group of related cases that deviate as a collective with regard to both numerical and categorical variables. Owing to its mixed data and potentially intricate relationships this type allows for a wide variety of complex anomaly subtypes. A *deviant class cycle* (ST-IXb) is an entire categorical subsequence that is anomalous, because it does not adhere to the overall cycle pattern. The *deviant shape sequence* (ST-IXf) is time series in a collection of multiple time series, with the anomaly located at the same position in the time space, but featuring an unusual form. There are many other Type IX anomalies, such as the *deviant subgraph* (ST-IXj), e.g. a group of linked vertices with significantly different substantive values than those observed in other parts of the graph. The *deviant spatio-temporal region* (ST-IXt) is a polygon or other aggregated object with substantive values that deviate when both its temporal pattern and spatial area are taken into account. An example is a region where the risk of suffering from a global disease outbreak is increasing significantly faster than elsewhere.