Quasi-identifier values can impact the severity of a data leakage. For example, a leakage involving diseases can have different impacts on individuals at certain stages of their lives. For example, a 96 year old with HIV is included in a data breach, which reveals his or her disease to the public. Disclosure of a disease can have varying consequences. Privacy of a minor is critical and it may be considered that information involving a minor may be more critical. Using L-Severity model only sensitive attributes are considered without any separation from quasi-identifiers or non-sensitive attributes. Non-sensitive attributes may be misclassified and can give more information than intended. Therefore, attaching a constant score for any added attribute can be beneficial when detecting for data leaks. A caveat of scoring severity is that the domain of these attributes and classifications must be maintained. If an attribute is misclassified an attac­­­­­­­­ker can target non-sensitive attributes to prevent detection. Tracking transactions within an application can alert an organization at the time a possible breach has occurred. A breach may go undetected until a victim reports a problem or an attacker advertises the data on the black market. **A DLP** may be tracking when sensitive data is released or based on some measurement of severity. Severity is complex and can involve many dimensions that are shared or specific to an industry. However, there are few a publications that focus strictly on the severity of only the data and the definitions of the impact of values for sensitive, quasi-identifier and non-sensitive attributes. Vavilis et al. created a model to quantify severity by attaching severity scores to values within a sensitive domain. L-Severity does not separate different classifications of the data. We propose a model that is more scalable allowing emphasis on other attribute classifications.

Giving a constant score to non-sensitive attributes can be useful when reading unstructured data. For example, an API can accept JSON objects that may have varying properties. Due to the unstructured format that the data can come in, unexpected attributes may be passed. Depending on how this data is used, extra information may be leaked or accidentally disclosed to an unauthorized user. An example could be a data dump of values that need to be emailed to another group or data that is passed into another system. This can cause system errors, rejections and leakages.

The comparison of the impact of the Dependency Factor (DF) in L-Severity was done against k-anonymity. This research did not find a significant impact on the severity when alternating algorithms. For example, if a table is conforming to k-anonymity the DF can also remain constant when. Having a higher DF metric will reduce the severity of a row. However, a higher DF score does not guarantee that a leaked table conforms to the k-anonymity rule. In order for a record to follow the *k-anonymity* rule, it must be part of a group of records that is at least *k* in size. After our analysis of M-Score’s DF metric and *k-anonymity* it was concluded that they are almost equivalent on the impact of the severity score. *K-anonymity* is a good baseline for measuring privacy within a generalized dataset. We attempted to measure the impact of considering how far off a group of records were from being conforming with *k.* The farther the number of unique quasi-identifiers a group of records is from *k,* the higher the severity will be. This correlates with a lower DF metric. For example, if there is only 1 distinguished record out of *n* records, *n/1* is greater than *n/k.* Assuming that *k* is larger than 1, this will result in a higher severity for a given record. Future research should be done on the impact of using *l-diversity*. [Sweeney] *L-diversity* provides privacy without knowledge of what the attacker may know. For example, the attacker may have strong background knowledge of the data.

Having the capability to attach weights to different classifications allows for more detailed analysis. For example, it is possible to weigh privacy higher than other data classifications. Classifications can include the traditional sensitive, quasi-identifier and non-sensitive attributes or attributes that are specific to an industry.

Define normal

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Job | City | Sex | Age | Disease | Medication |
| Student | LA | Male | 100 | HIV | Vitamins |
| Student | LA | Male | 20 | Heart Attack | Aspirin |
| Student | LA | Male | 30 | Migraine | Paracetamol |
| Student | LA | Male | 40 | Hypertension | Aspirin |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Job | City | Sex | Age | Disease | Medication |
| Student | LA | Male | 10 | HIV | Vitamins |
| Student | LA | Male | 20 | Heart Attack | Aspirin |
| Student | LA | Male | 30 | Migraine | Paracetamol |
| Student | LA | Male | 40 | Hypertension | Aspirin |

In case 1 and case 2 both leaked tables conform to 1-anonymity. All values are equal except for the age in record 1 for case 2. Using the L-Severity model that Vavillis et al. proposes, the severity of the two tables would be equal. This may be due to a fault in the proposed scores.