Information Models for Large Table Trimming

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- Motivation -

Trimming large datasets:

- Slow web backends that deal with live data aquisition
- ML sampling of training data
- anomaly detection/filtering

Requirements:

- Reduce the number of rows as much as possible
- Keep as much information as possible

Result: best compromise between size and retained information

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Model:

- Information function: what we value
- Trimming procedure: order of discarding

Dataset:

- Classes: include data with the same meaning (table columns)
- Entries: one piece of data (table cell)
- Timestamps: mark the order (and frequency) of rows
- Events: data captured at the same time, hence placed in the same row (table row = timestamp + event)
- Correlations: common patterns in entries → cross-referencing

Time symmetry: attention factor

- neutral: older and newer events are equally important
- elevated: older events are less important than newer events
- low: older events are more important than newer events

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Information function:

- non-negative value for any amount of data
- adding events does not decrease the information; trimming events does not increase the information
- trimming the lowest information event results in minimum decrease the dataset information

Conclusion: total information is a sum-like function of event information

Cross-referencing: binary match (identical/different)

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Combinatorial subset optimization problem:

- exact solution is **impractically slow** for large datasets
- practical solution: greedy algorithms and derived refinements

Greedy algorithm accelerators: **trimming strategy**:

- event trimming: discards the event with lowest information in each iteration, then recalculates the contributions; slow; good memory
- block trimming: discards some of the events with low information in each iteration, then recalculates the contributions; faster; minimal memory loss
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- Based on Shannon information applied to entire events
- Assumes that the data is ergodic (all the events are equally important), so the timestamp column is ignored by the information function
- Ergodicity can be broken by the procedure
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- Shannon information is applied at entry (table cell) level
- Cross-referencing weights are introduced to Shannon information to emphasize entries in one class (column) appearing also in other classes
- Event information is a sum of entry contributions
- A block trimming strategy is developed based on KMeans clustering low information contribution events in blocks and eliminating them in one iteration
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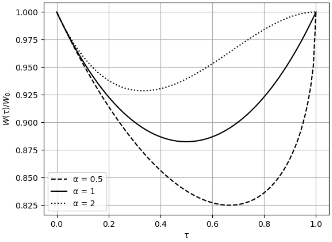
- The Ideal perception Model -

- Development of the Class Statistical Model with additional weights to account for timestamp distribution of repeated appearences of the same value in a class
- Timestamp distribution weights are calculated to mimic human perception (forgetting, memory reinforcement by repetition)



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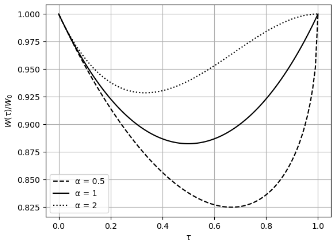

Conclusions

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- Compromise between the amount of trimming and the amount of information loss should be achieved.
- Information models structure should mimic the data consumption purpose.
- A computation speed-up can be obtained by using various trimming strategies with the greedy algorithm.

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