HOW UNIQUE ARE YOU ON TWITTER

UNDERSTANDING THE TRADEOFFS BETWEEN PRIVACY AND UTILITY

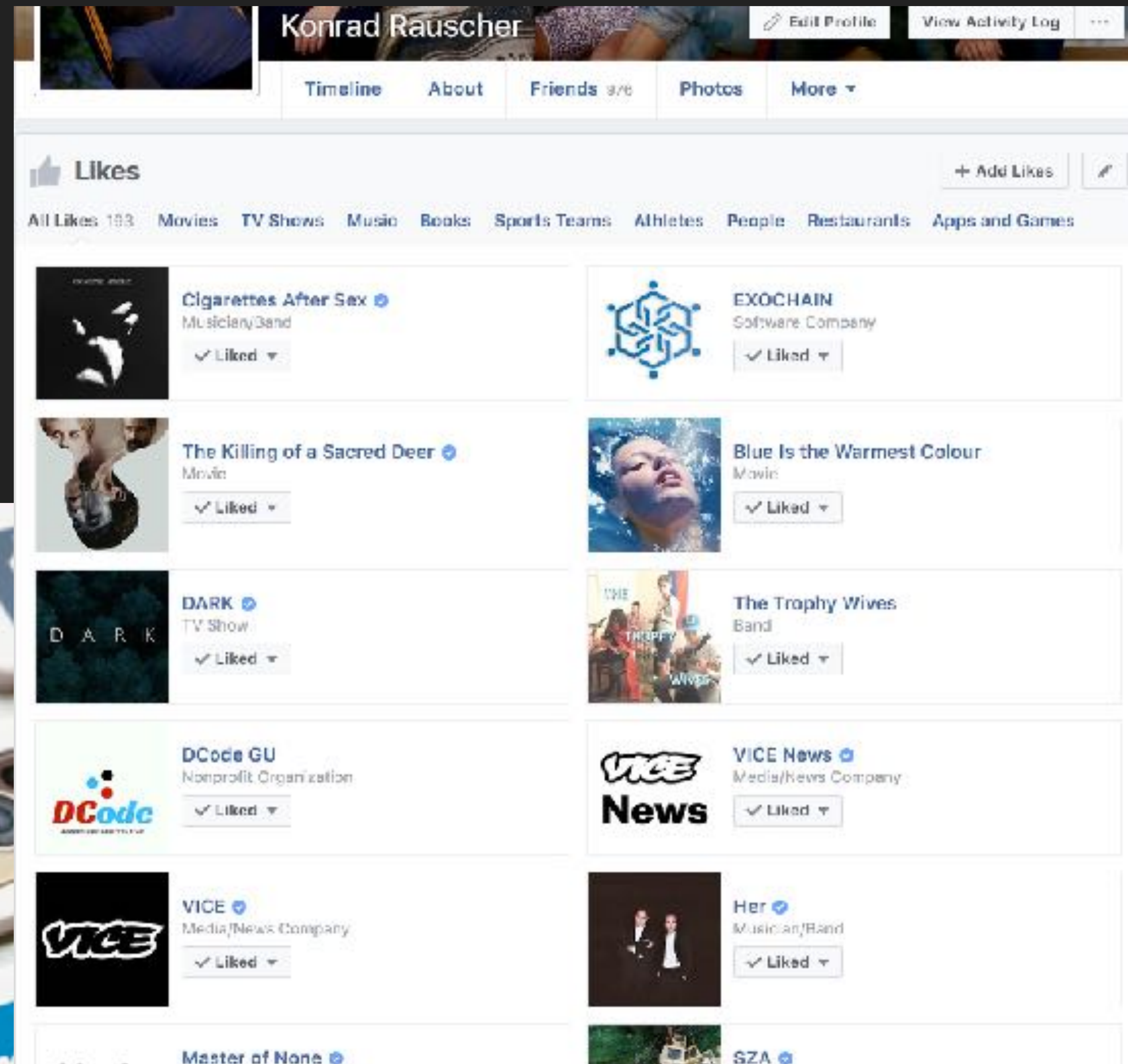
- KONRAD RAUSCHER

OUTLINE

1. Motivation & Problem
2. Related Literature
3. Methodology
4. Data Description
5. Experiments & Results
6. Contributions

MOTIVATION

Cambridge Analytica



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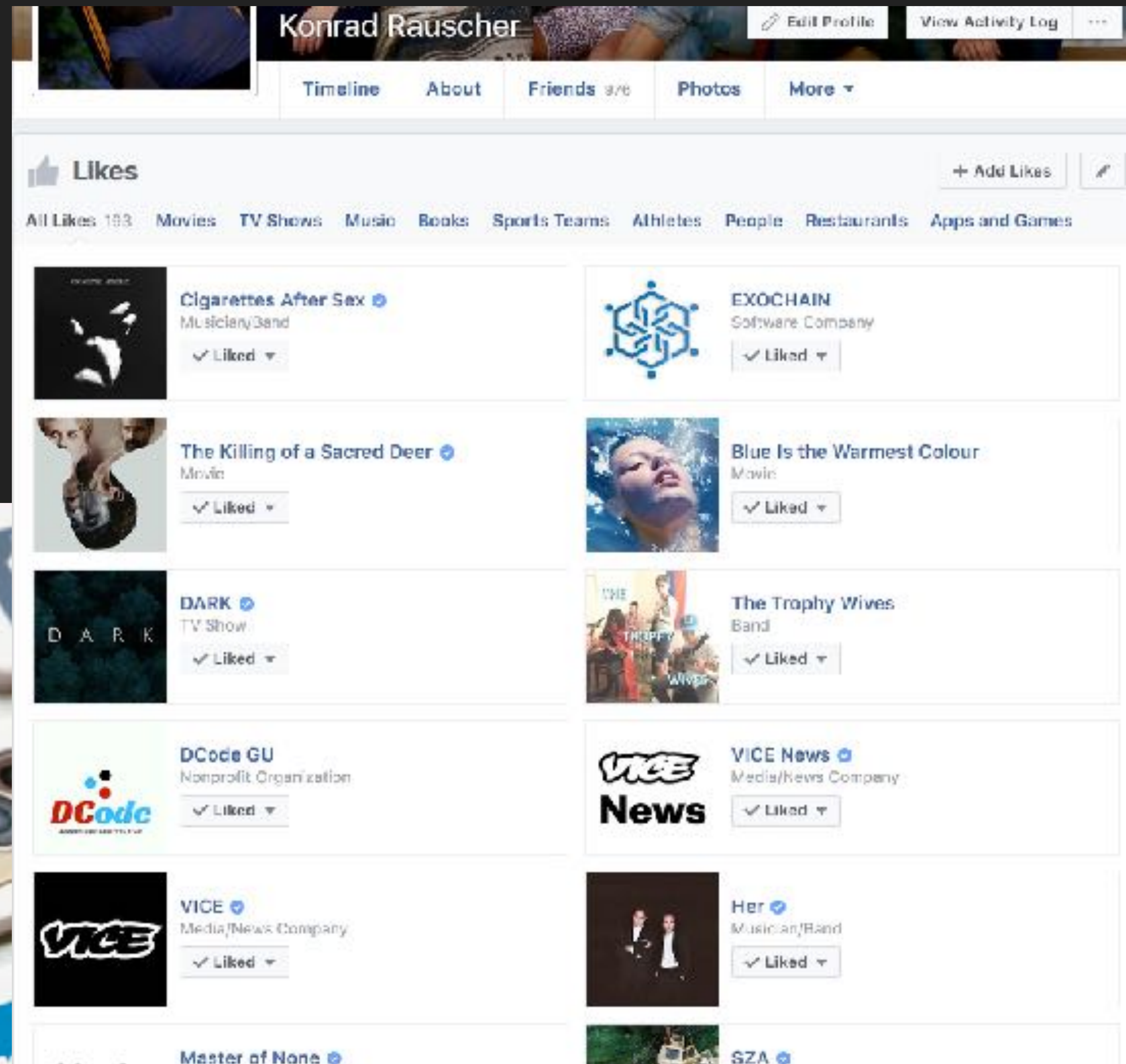
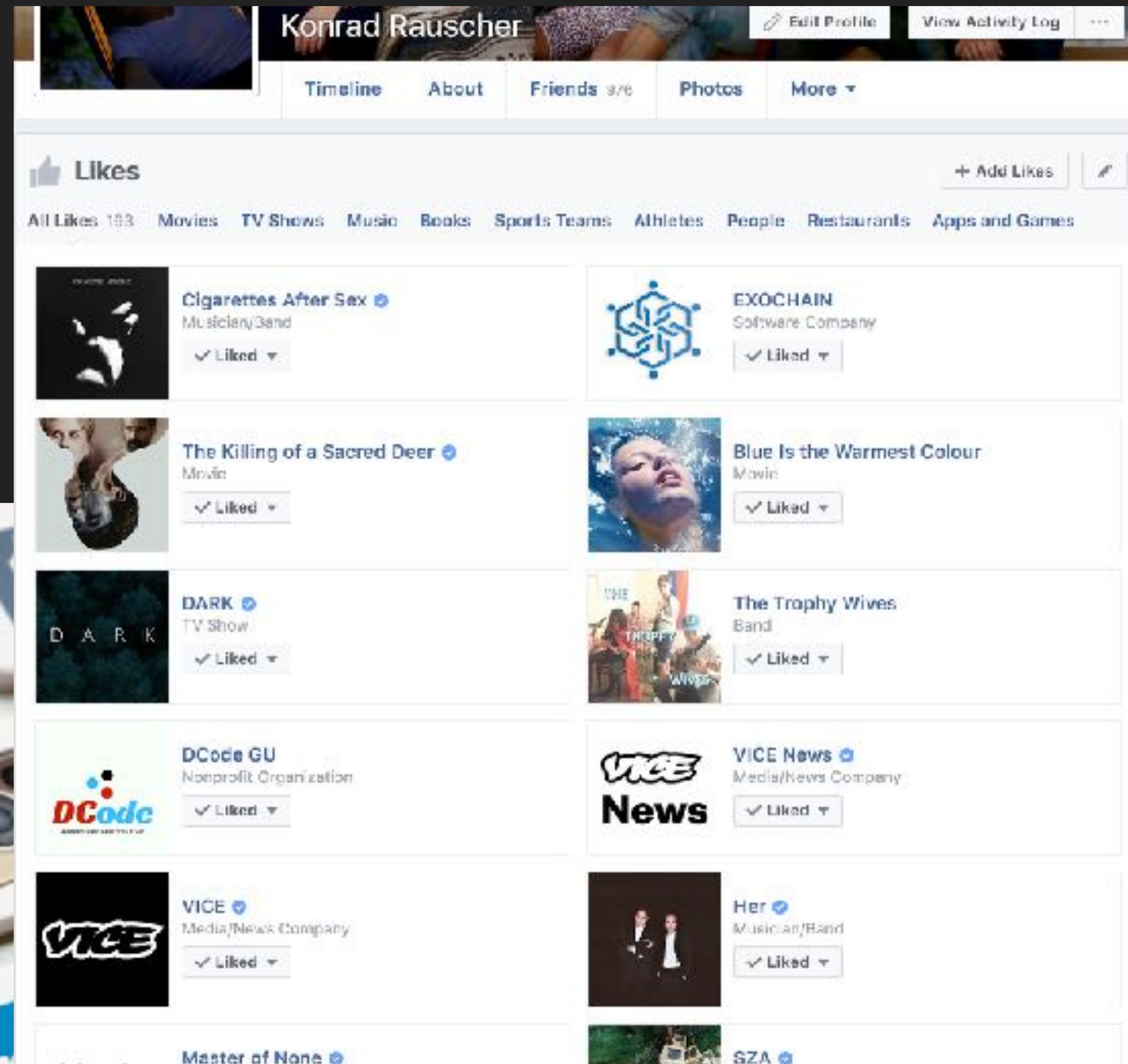


How unique is Twitter user content?

MOTIVATION

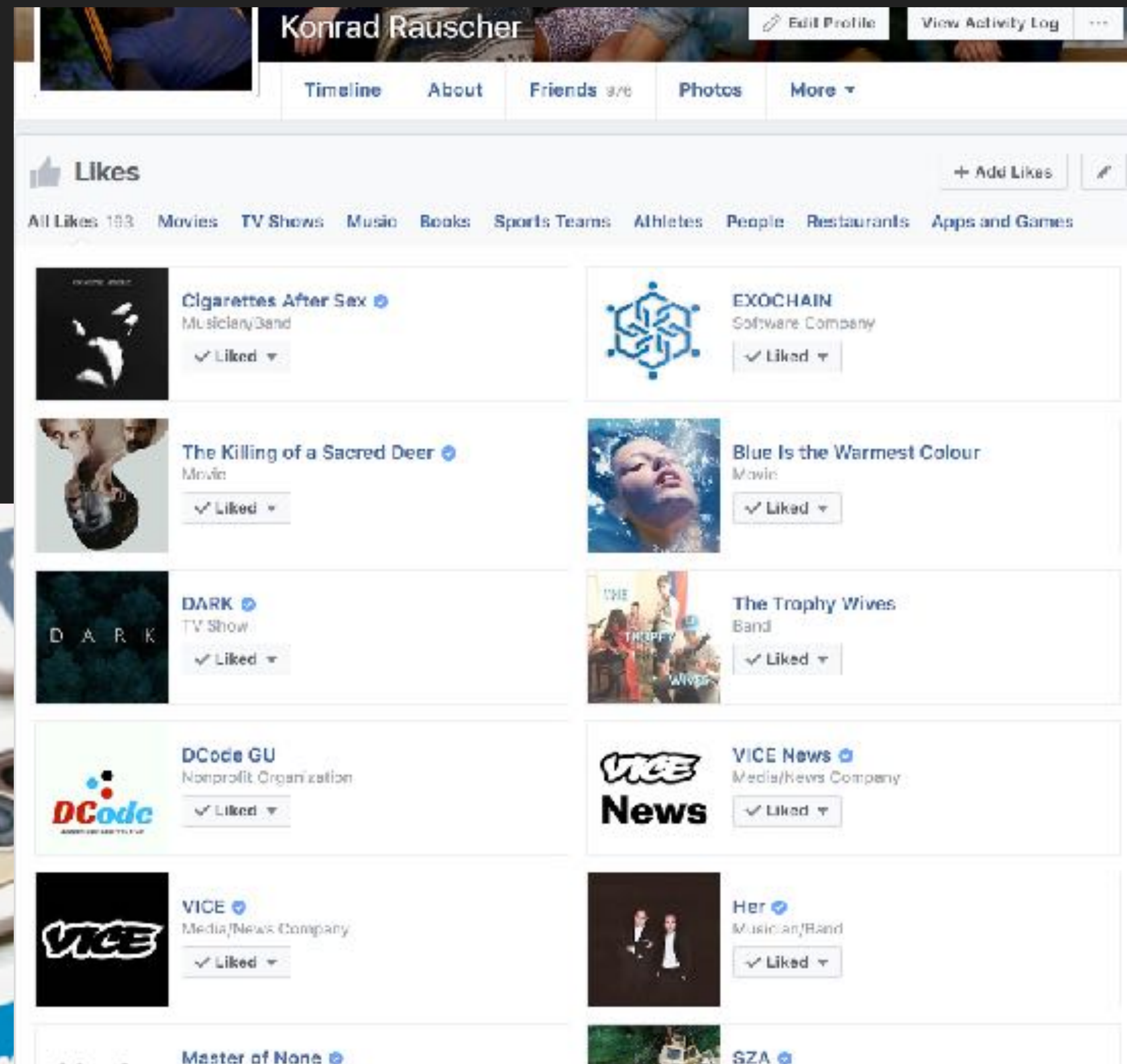
Cambridge Analytica



Can we easily make it private?

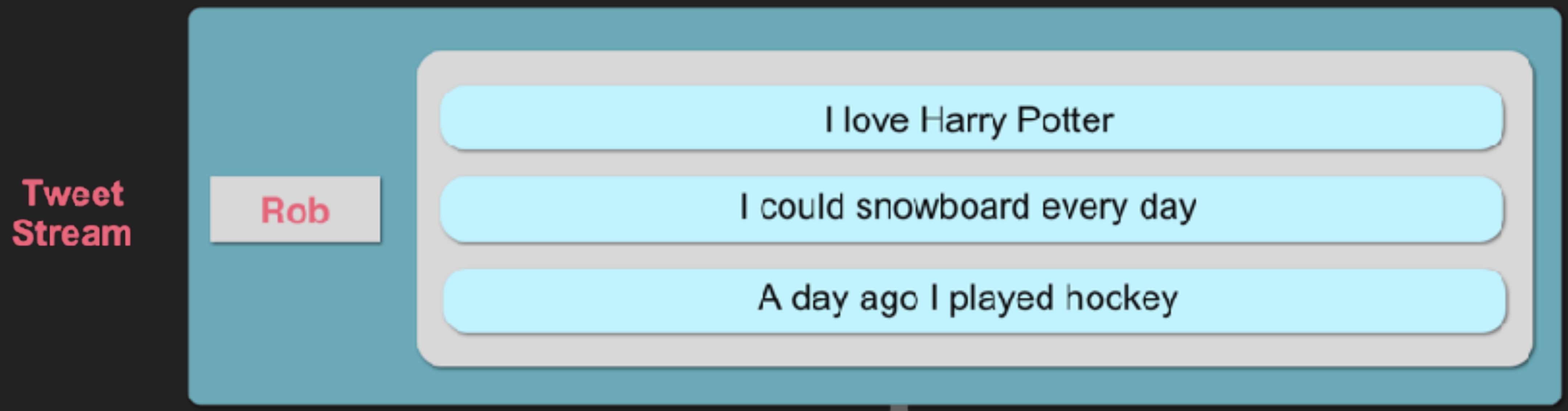
MOTIVATION

Cambridge Analytica



If so, still retain data utility?

EXAMPLE – UTILITY & PRIVACY OF TWEET STREAMS



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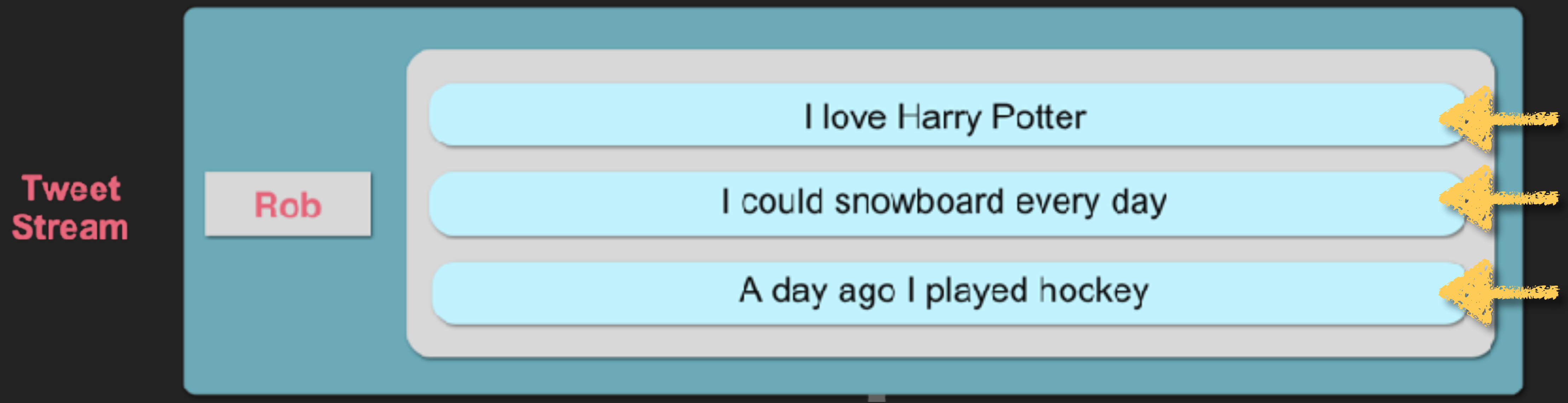

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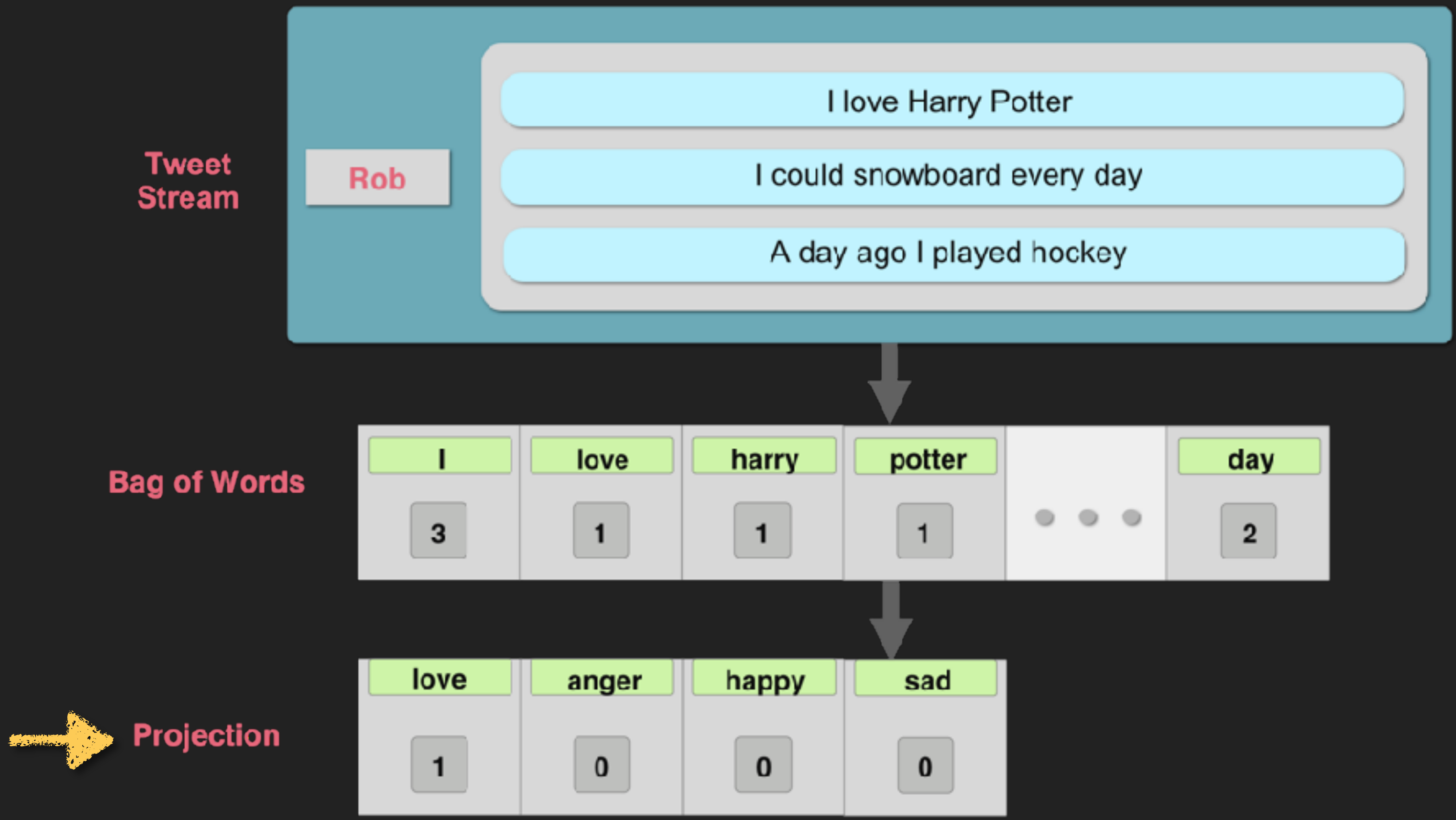


PROBLEM: TRADE-OFFS BETWEEN PRIVACY AND UTILITY

- Given a set of Twitter users, determine the tradeoff between **privacy** and **utility** by considering different projections of their tweet streams

RELATED LITERATURE

RELATED LITERATURE – PRIVACY

- Evaluate how much information is revealed by directly publishing data on the web [Singh et al., 2015]
  - Small number of social media attributes can allow for unique identification
- Measure privacy and utility loss arising from anonymization techniques utilized in microdata publishing [Li and Li, 2009]
  - Privacy is an individual concept and utility an aggregate concept
- Proposal of k-anonymity privacy measure [Sweeney, 2002]

RELATED LITERATURE - EMOTION

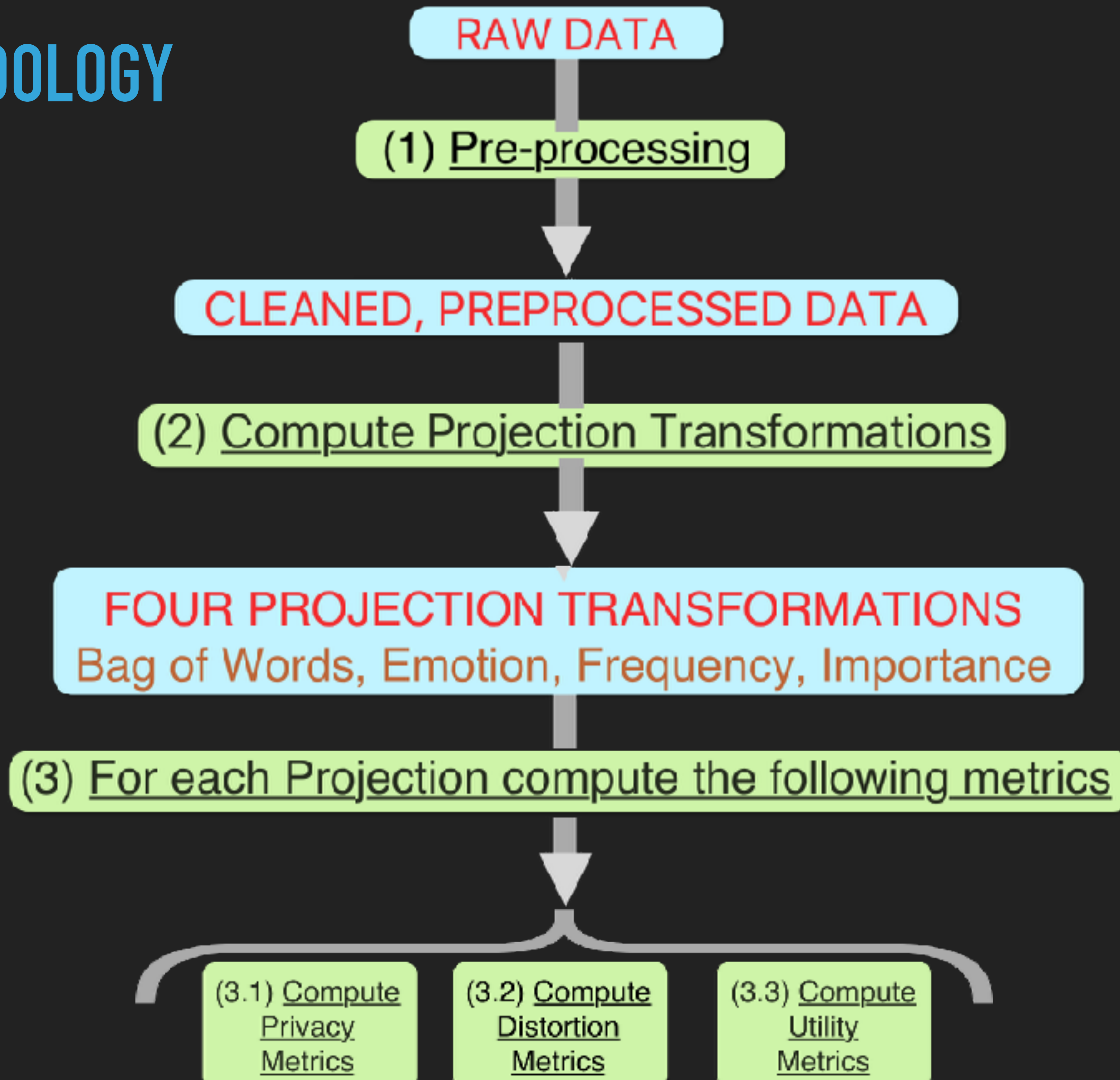
- Propose a bootstrapping algorithm to learn hashtags that convey emotion [Qadir and Riloff, 2013]
- Demonstration of positivity bias in human emotion [Doddsa et al.]
- Propose several challenges unique to the classification of individual emotions [Roberts et al., 2012]
- Propose methods for the construction and evaluation of emotional lexicons that use emoji [Yang et al., 2007]

RELATED LITERATURE – TEXT SUMMARIZATION

- Evaluation of novel word-based text compressions in terms of speed and achieved compression factor [Horspool and Cormack, 1992]
- Evaluation of word-based text compressions in terms of subjective quality [Witten et al., 2005]

METHODS

GENERAL METHODOLOGY



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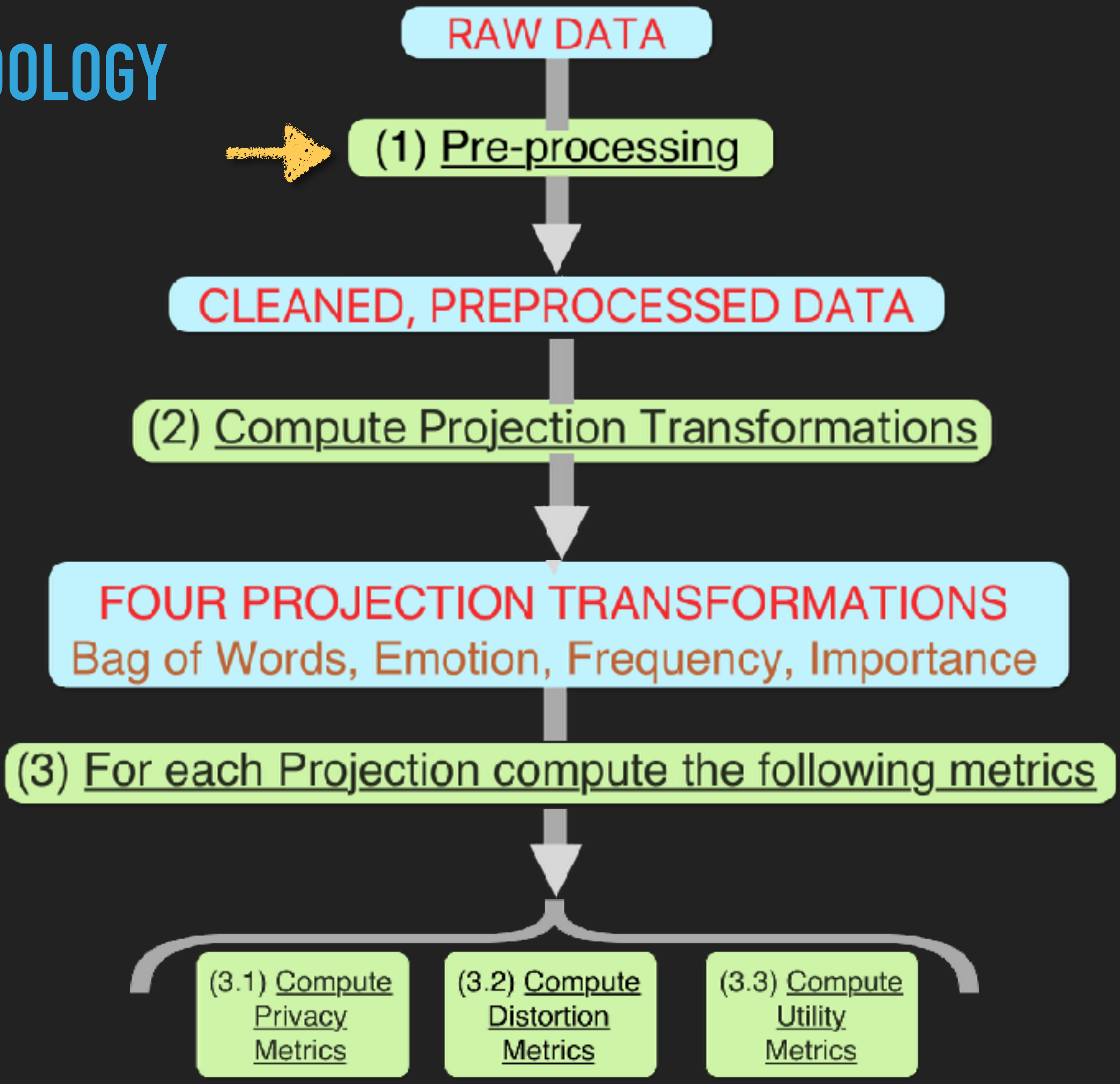

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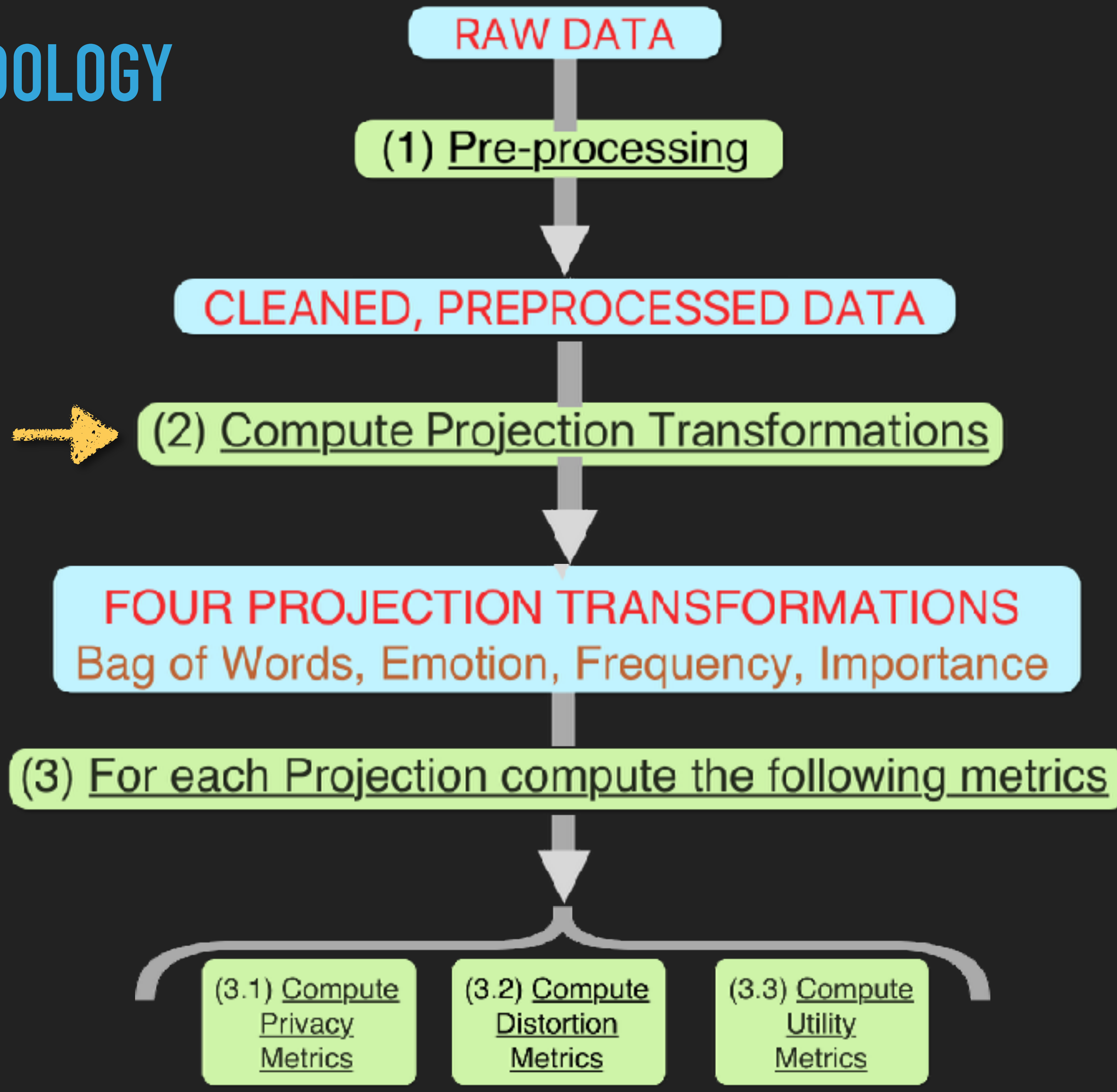

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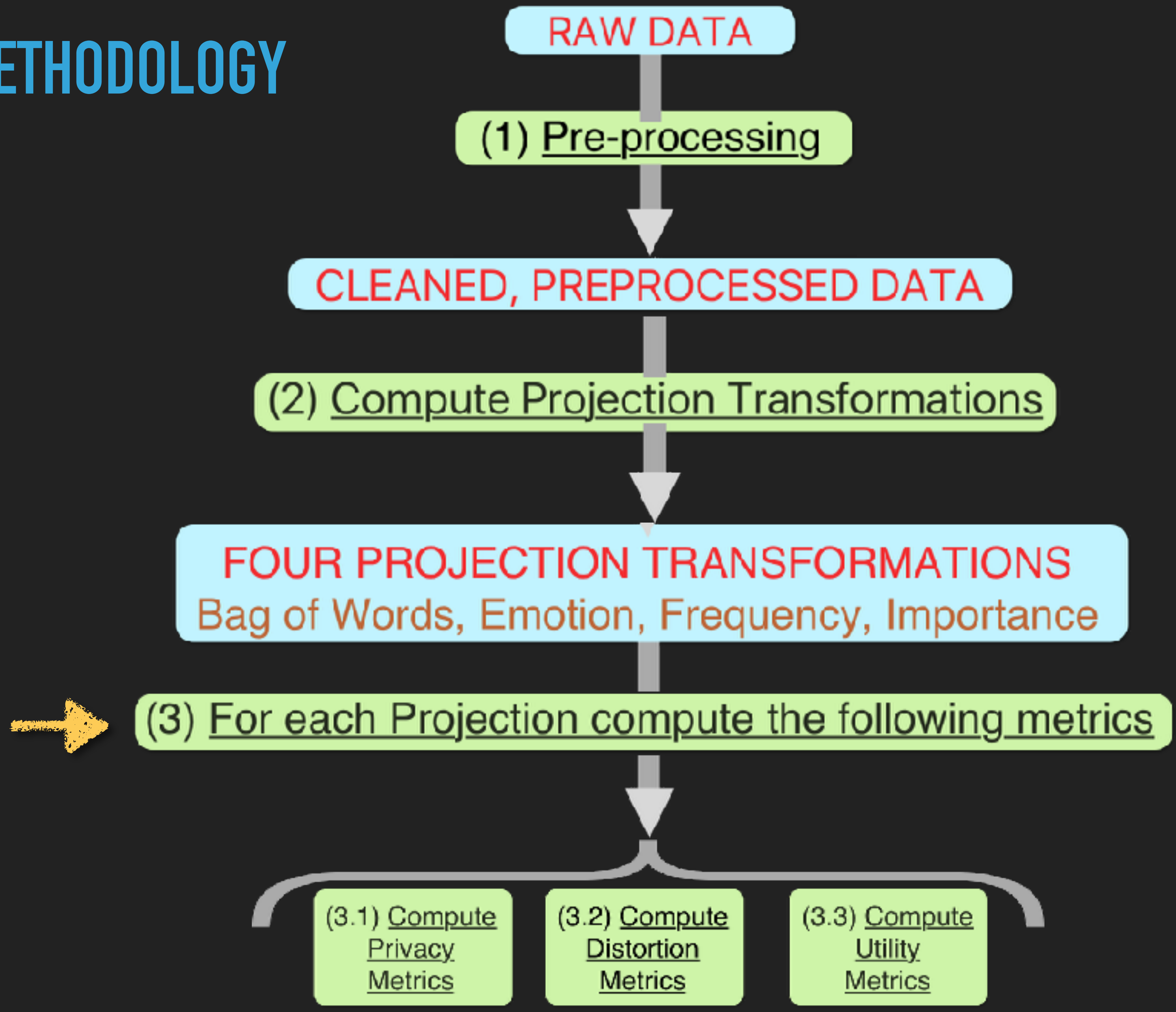

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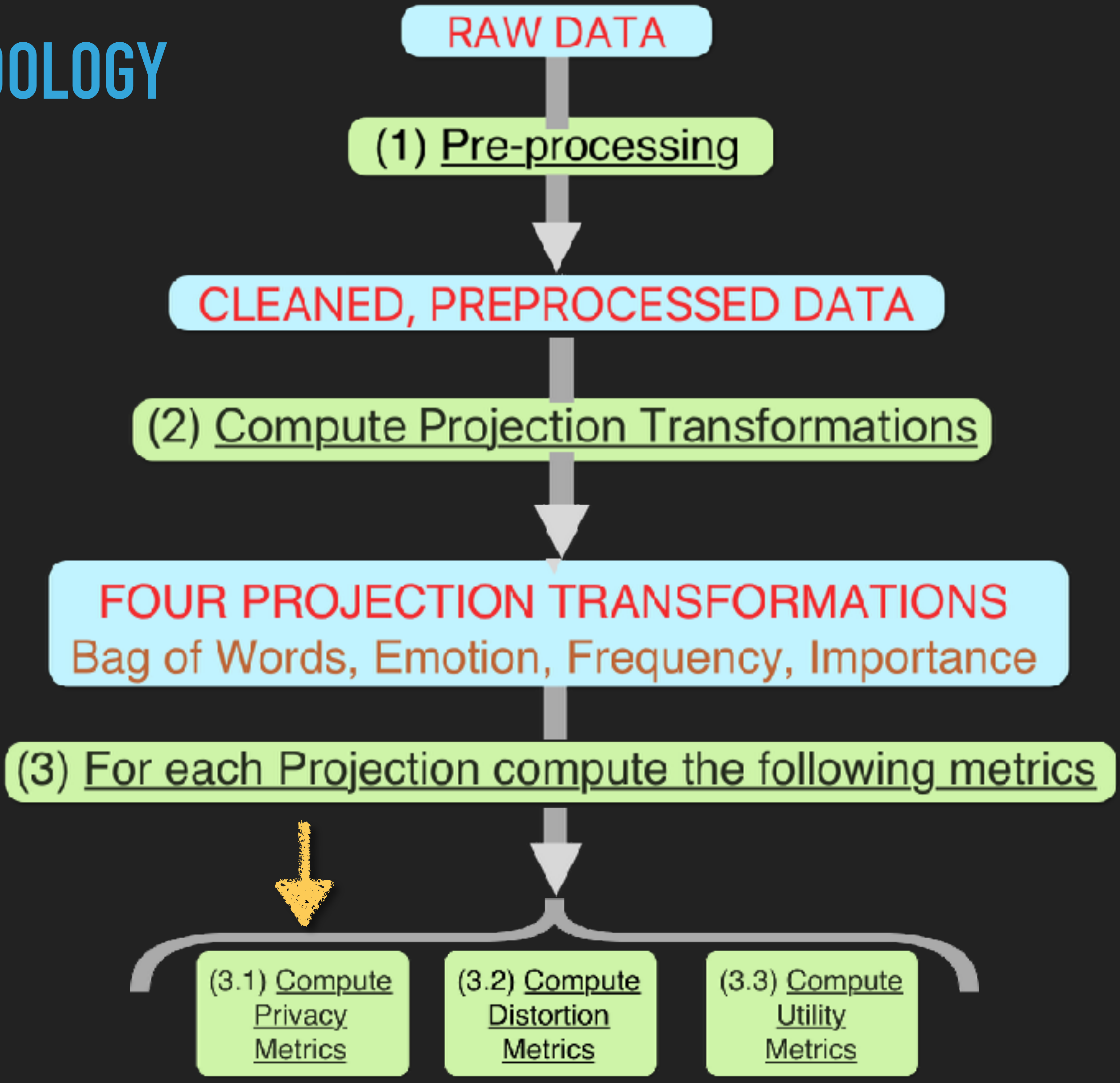

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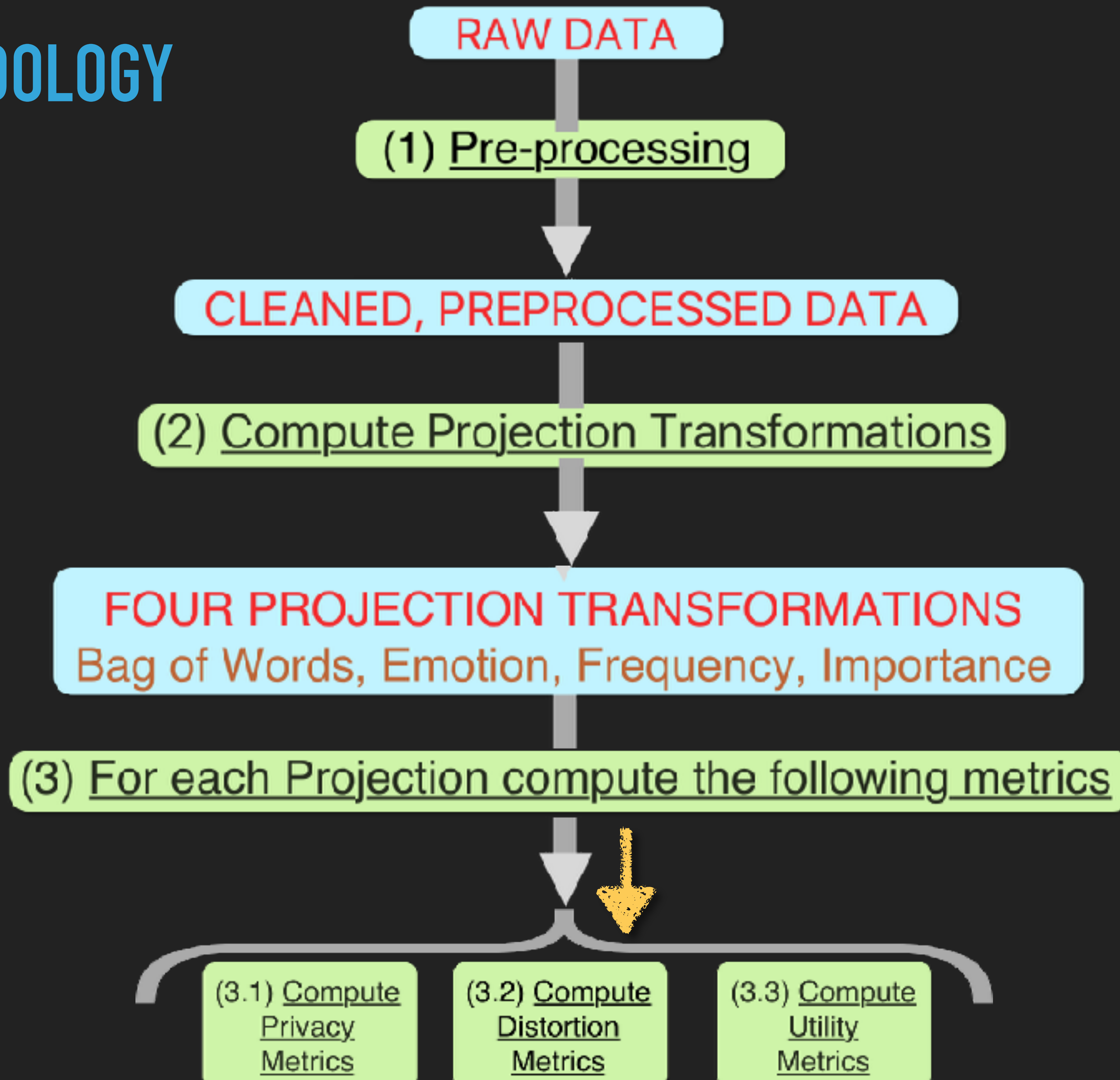

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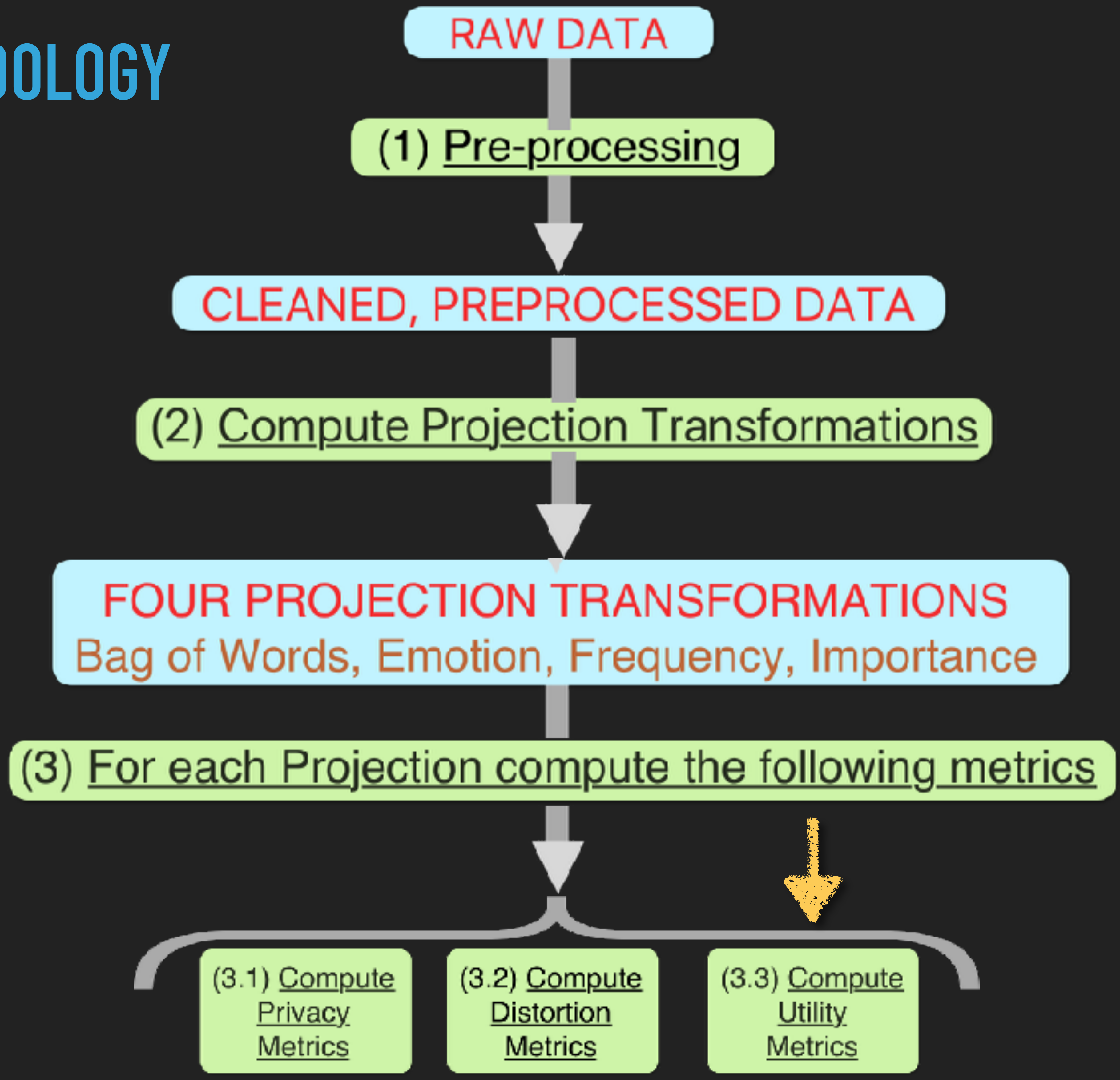

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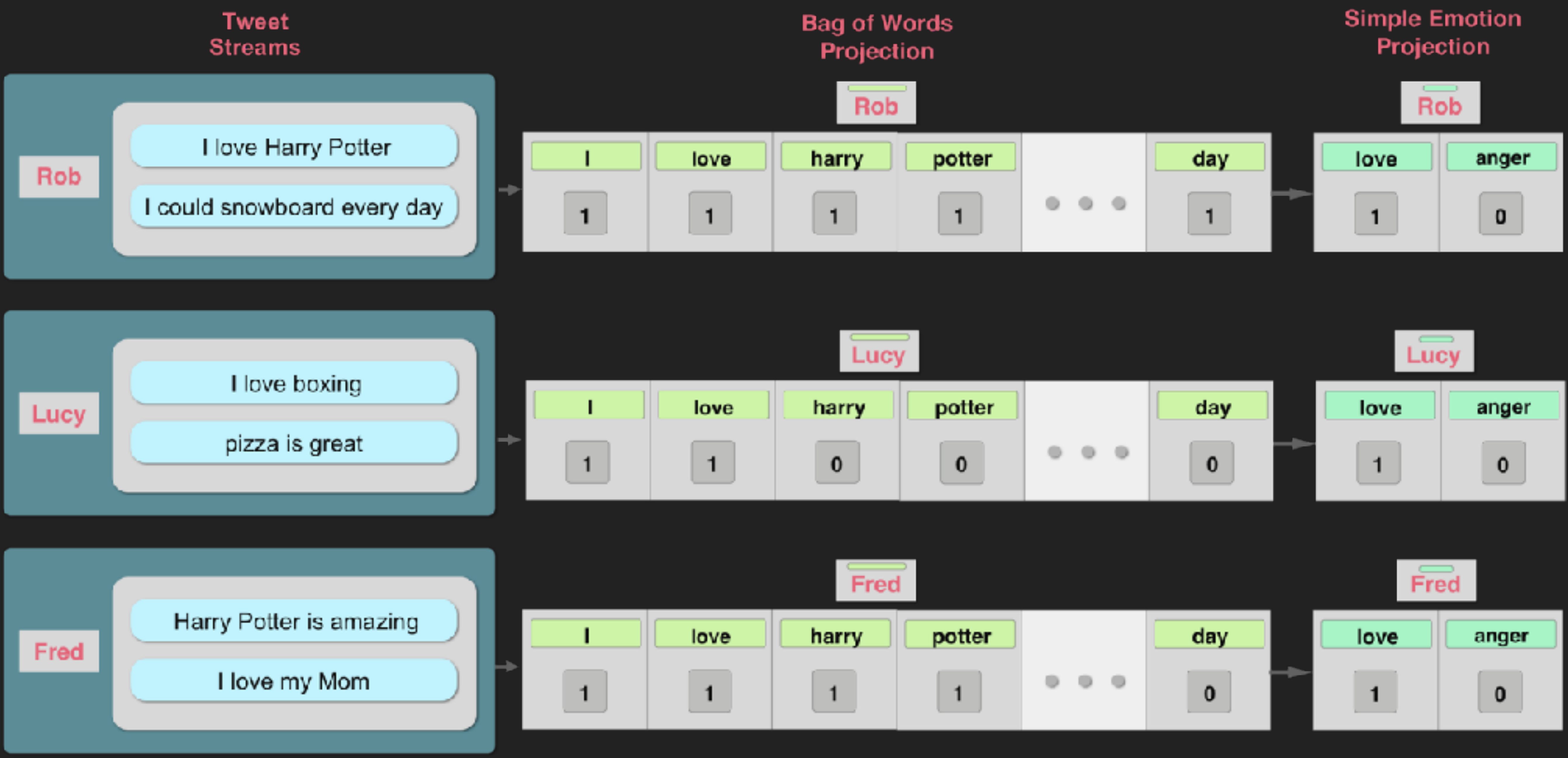

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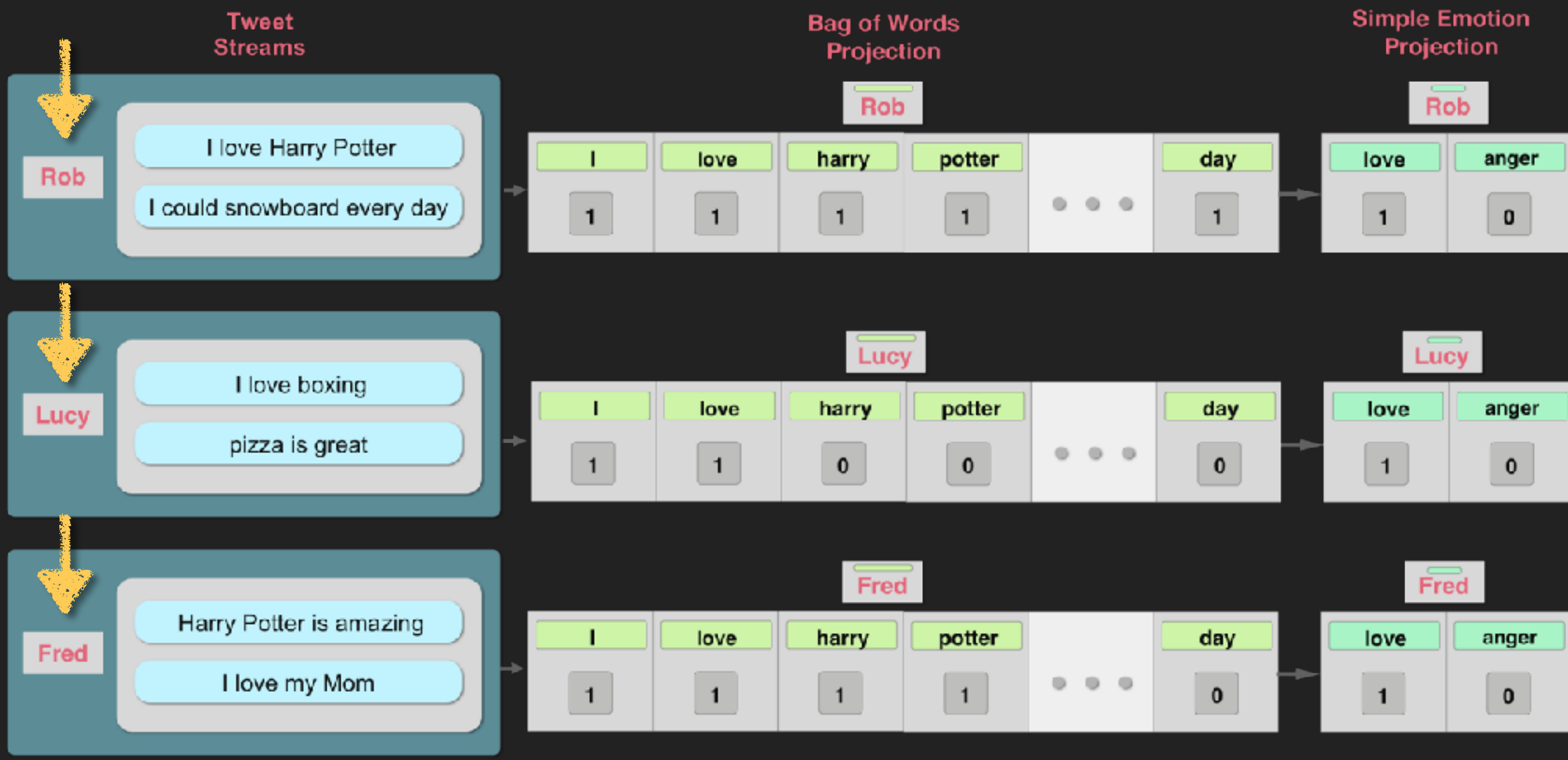

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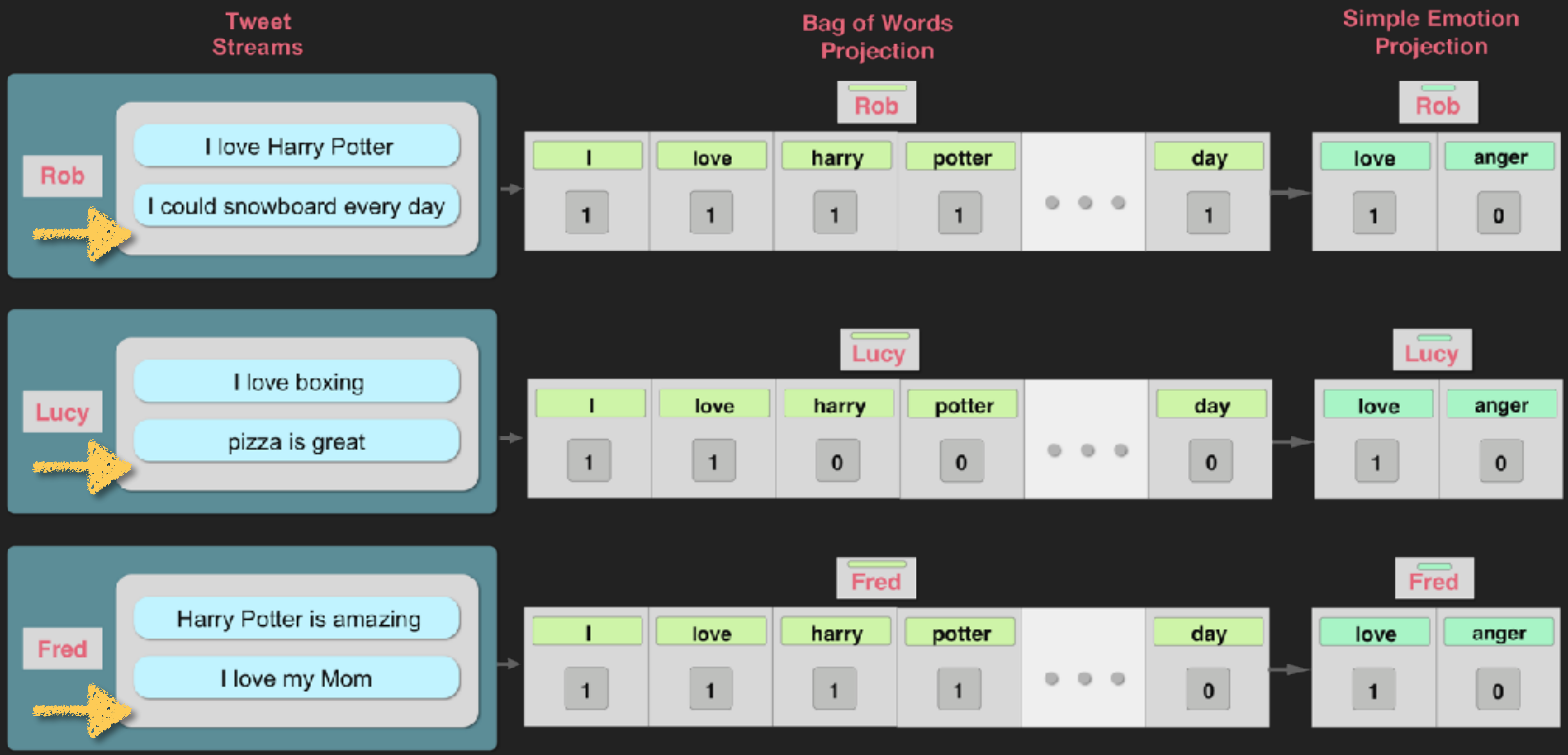

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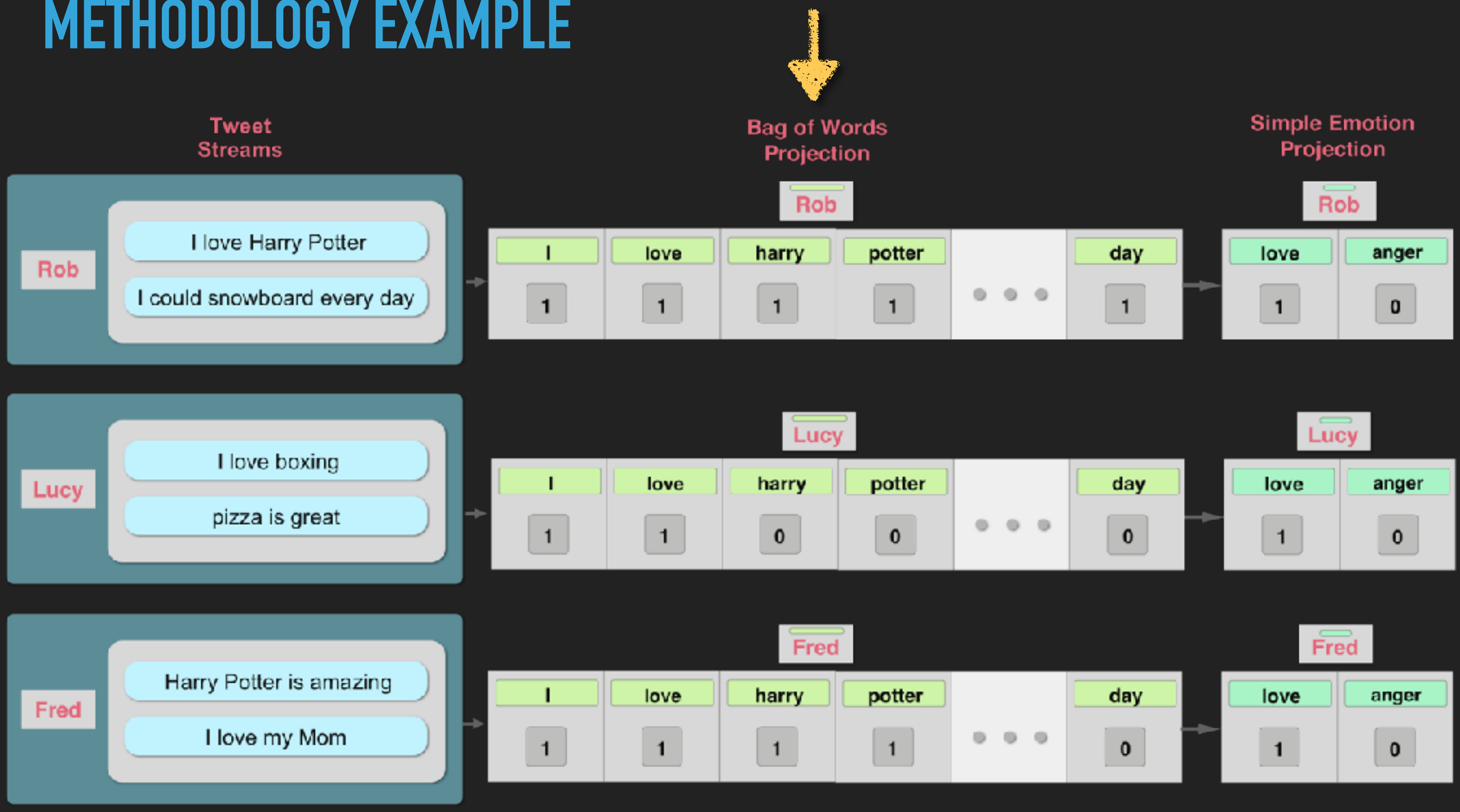

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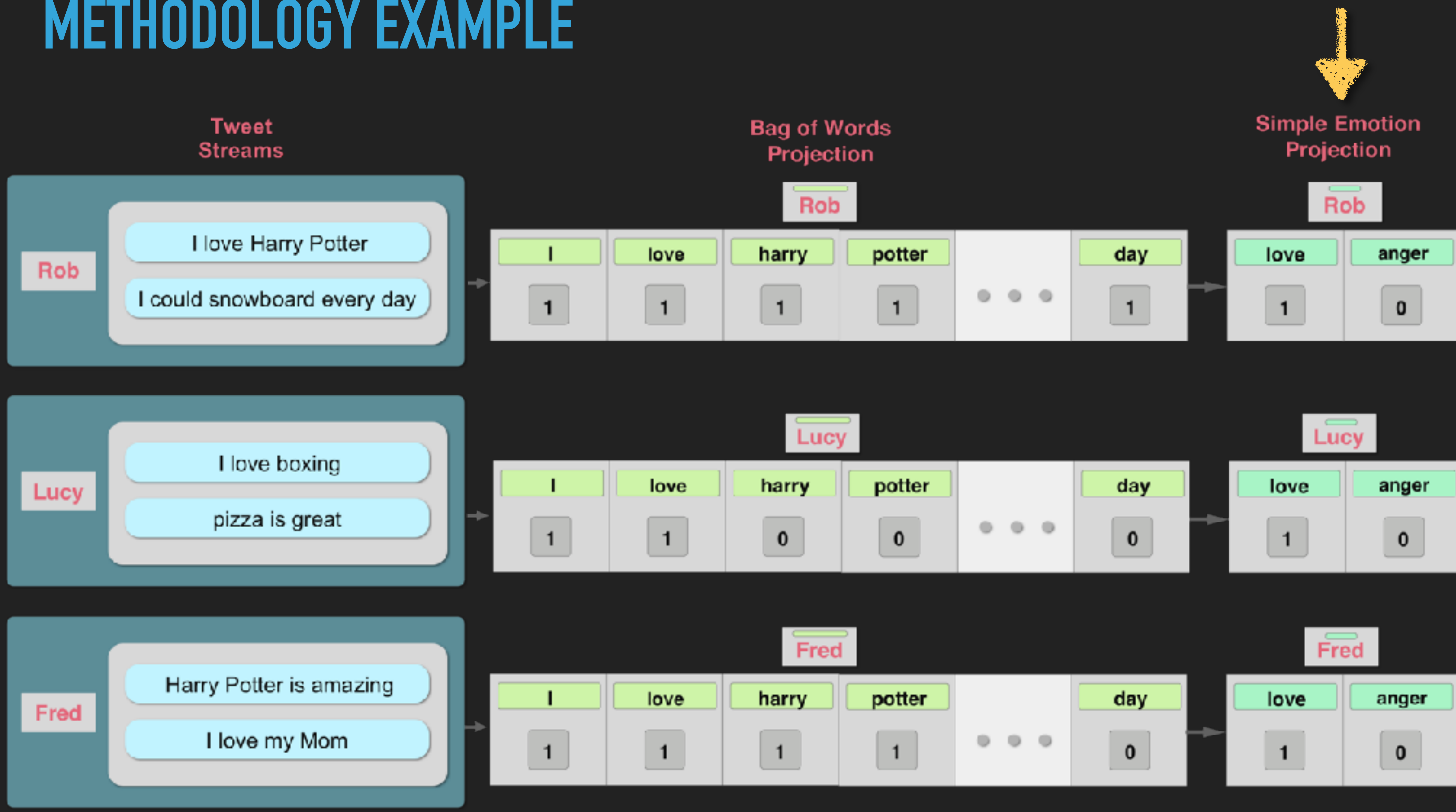
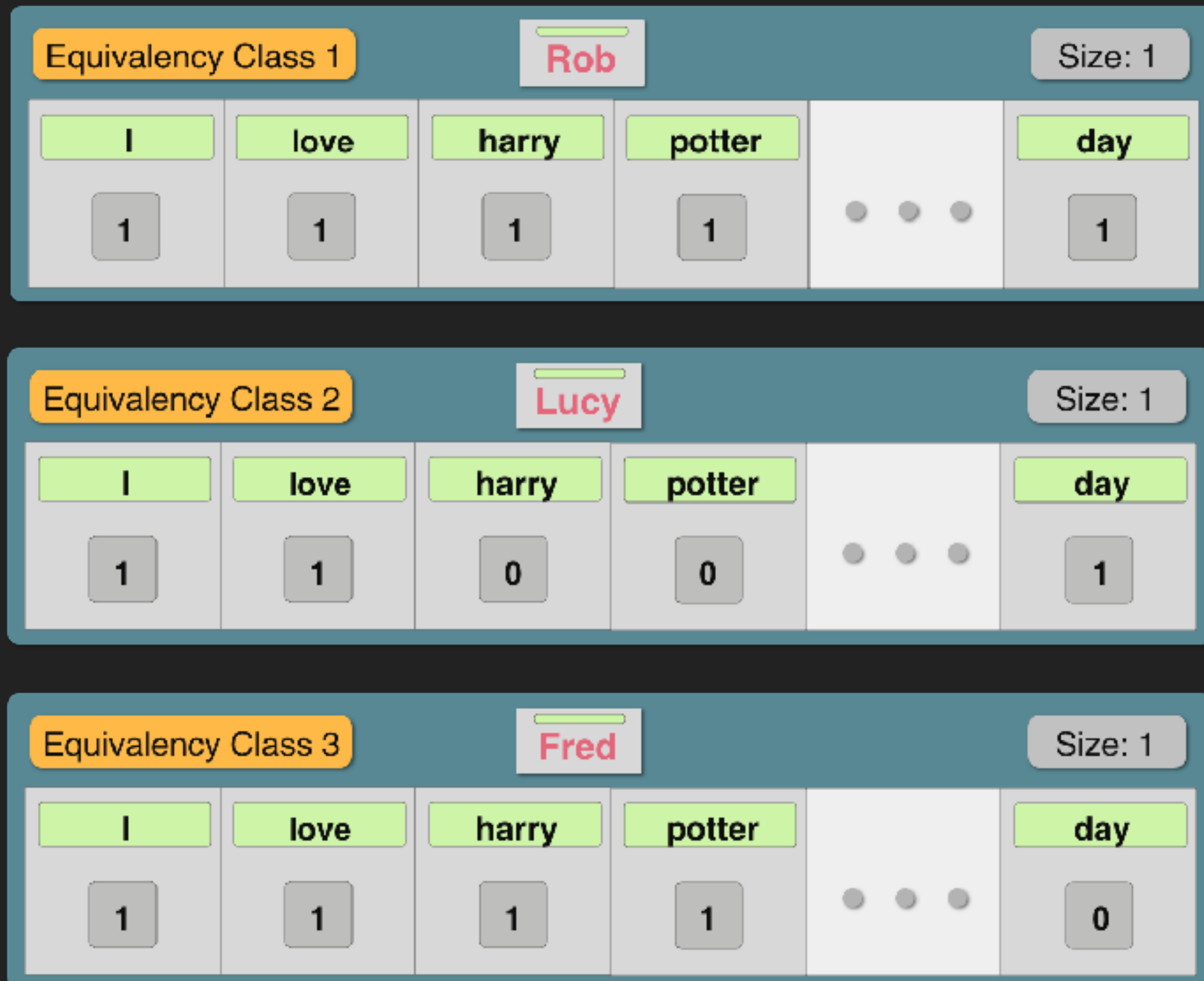


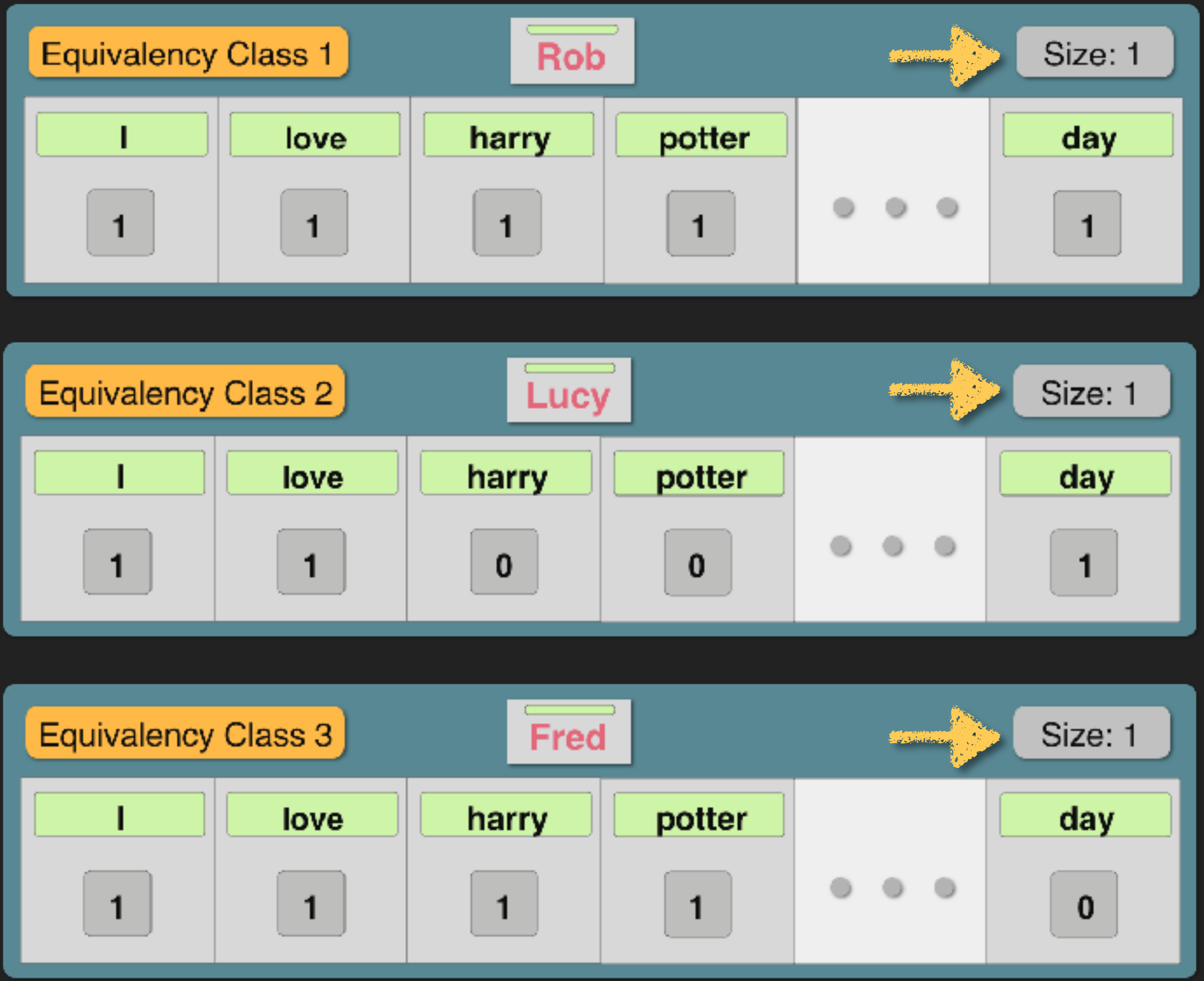
METHODOLOGY EXAMPLE – PRIVACY

- Bag of Words



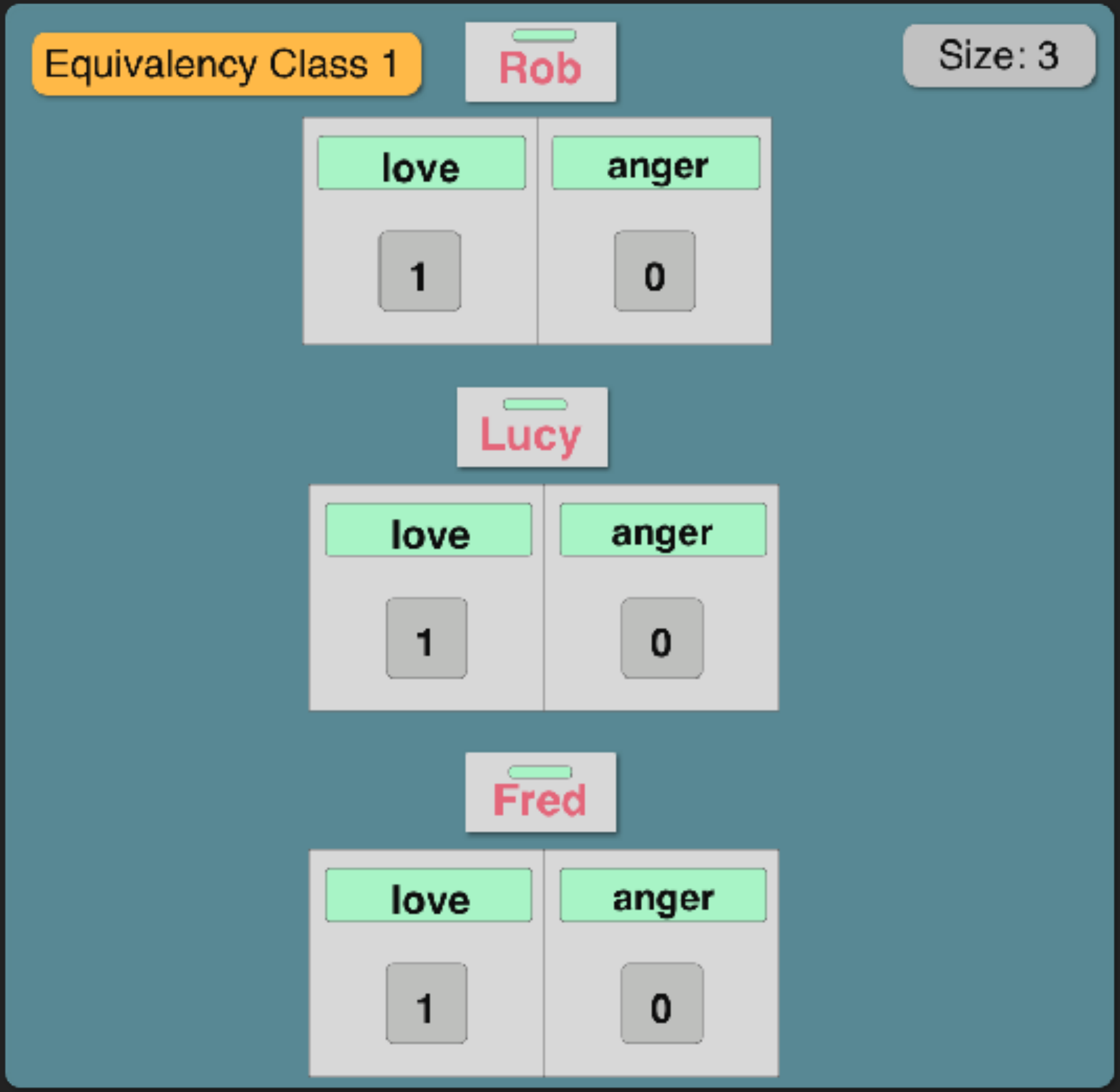
METHODOLOGY EXAMPLE – PRIVACY

- Bag of Words
- Lowest size equivalence class is 1
- k=1 for k-anonymity of the vector space



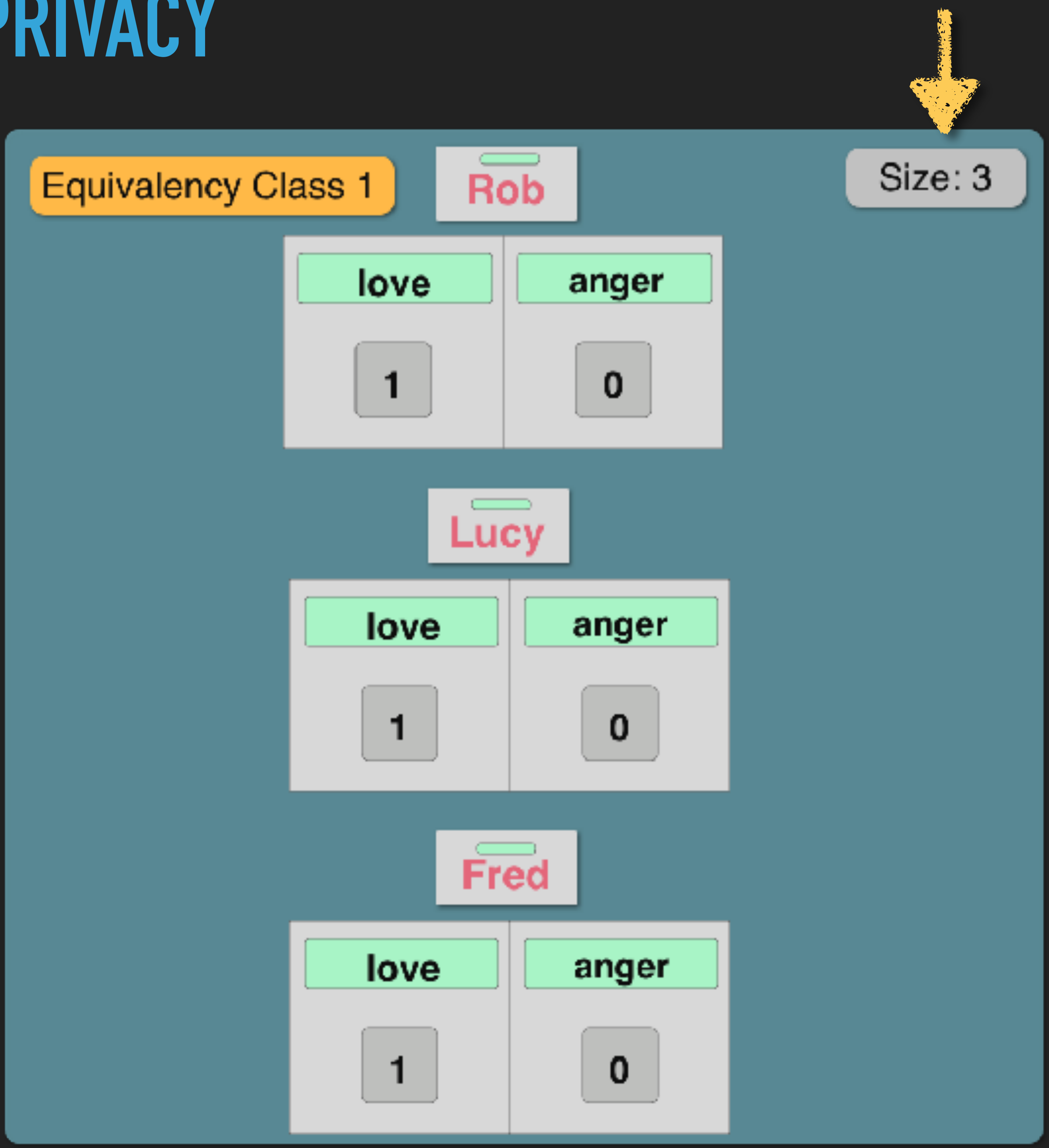
METHODOLOGY EXAMPLE – PRIVACY

- Emotion Projection



METHODOLOGY EXAMPLE – PRIVACY

- Emotion Projection
- k = 3 for k-anonymity of the vector space



DISTORTION

- Projections of tweet streams result in distortion
- Loss of potentially distinguishing features
- High distortion, fewer features to distinguish an individual

UTILITY

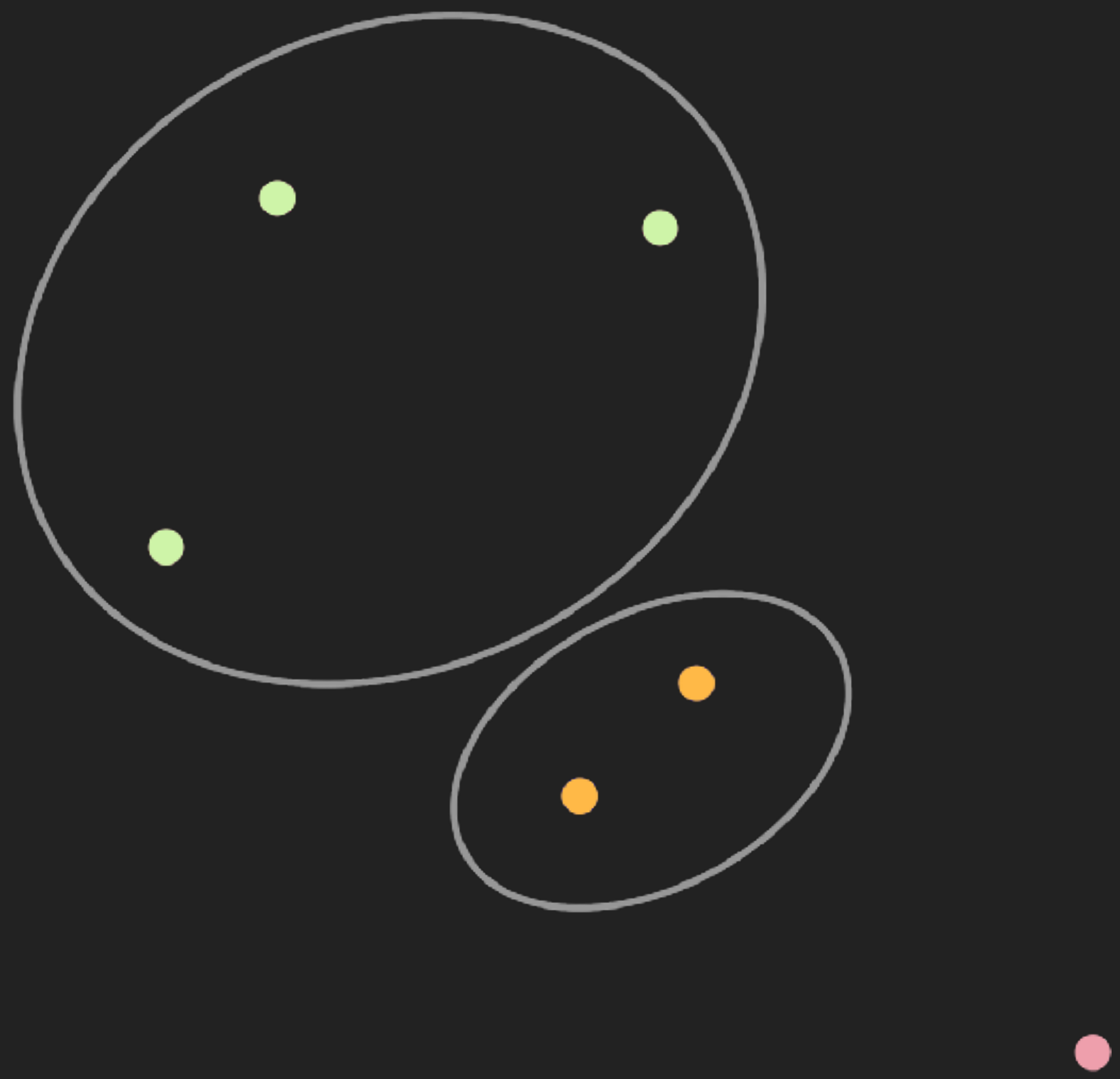
- Clustering
- Anomaly Detection
- Frequent Item Set Mining

CLUSTERING – K MEANS

- K Means [Lloyd, 1957]
  - Aims to partition *n* observations into *k* clusters
  - Each observation belongs to cluster with nearest mean

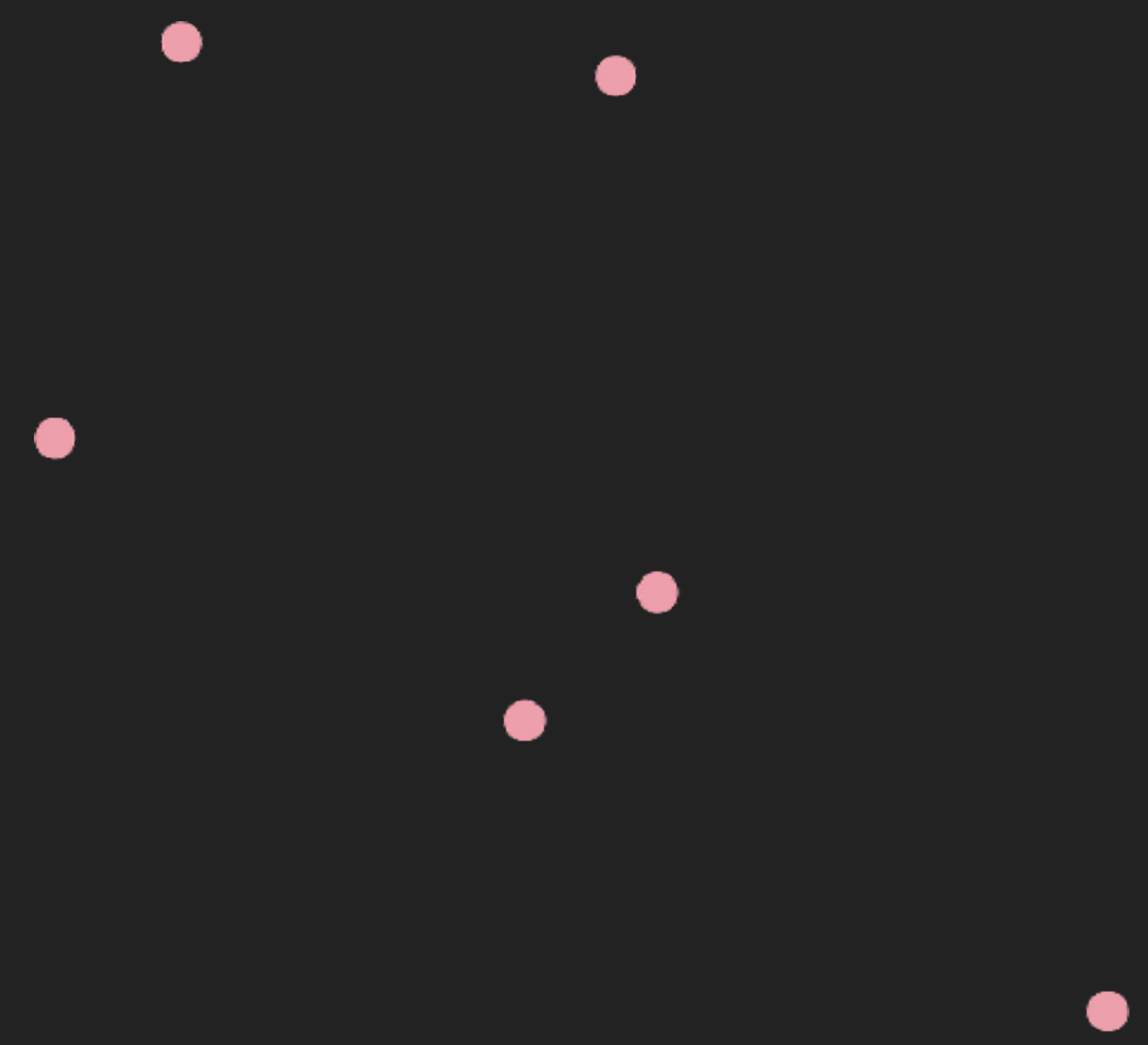
CLUSTERING – K MEANS

- k = 2



ANOMALY DETECTION – LOCAL OUTLIER FACTOR

- Local Outlier Factor [Breunig et al., 2000]
  - Observations evaluated according to density of their neighborhood
  - The lower the density of observations near an observation, the more anomalous the observation



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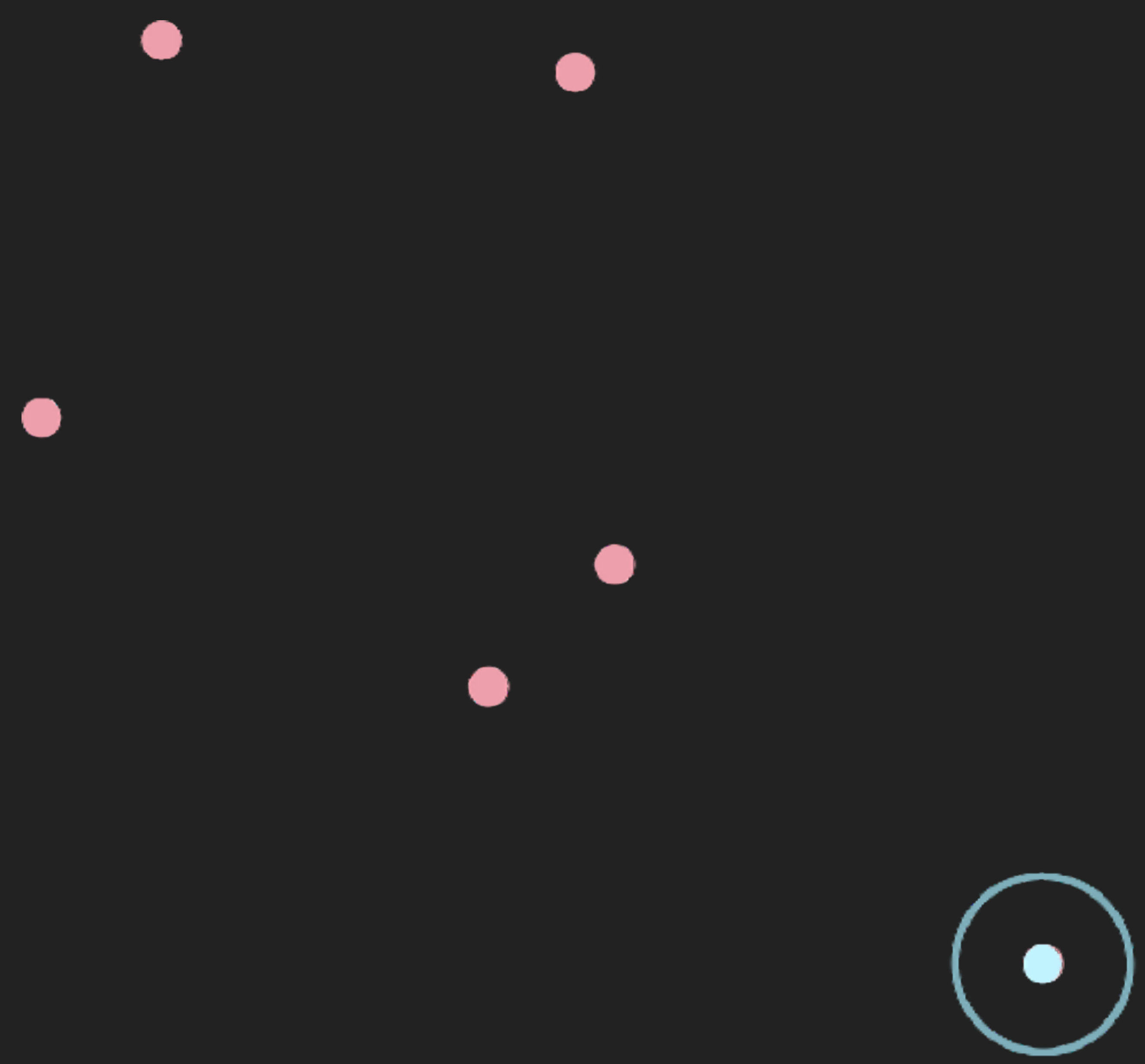

FREQUENT ITEM SET MINING

- Frequent Item Set Mining [Agrawal et al., 1993]
  - Compute sets of features that co-occur above a specified frequency (minimum support)

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I love Harry Potter

I could snowboard every day

I love hockey

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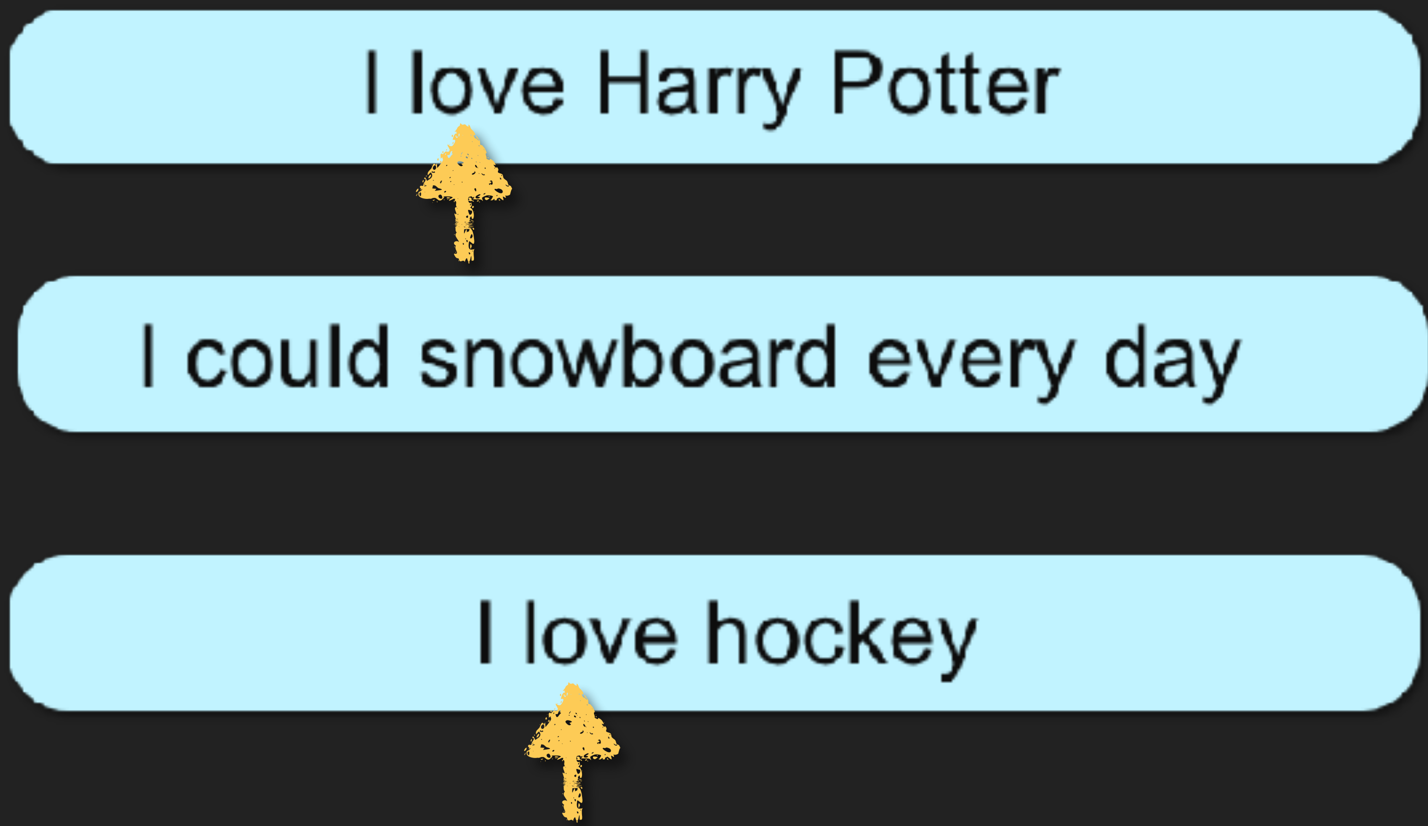

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METHODOLOGY - UTILITY & DISTORTION EXAMPLE

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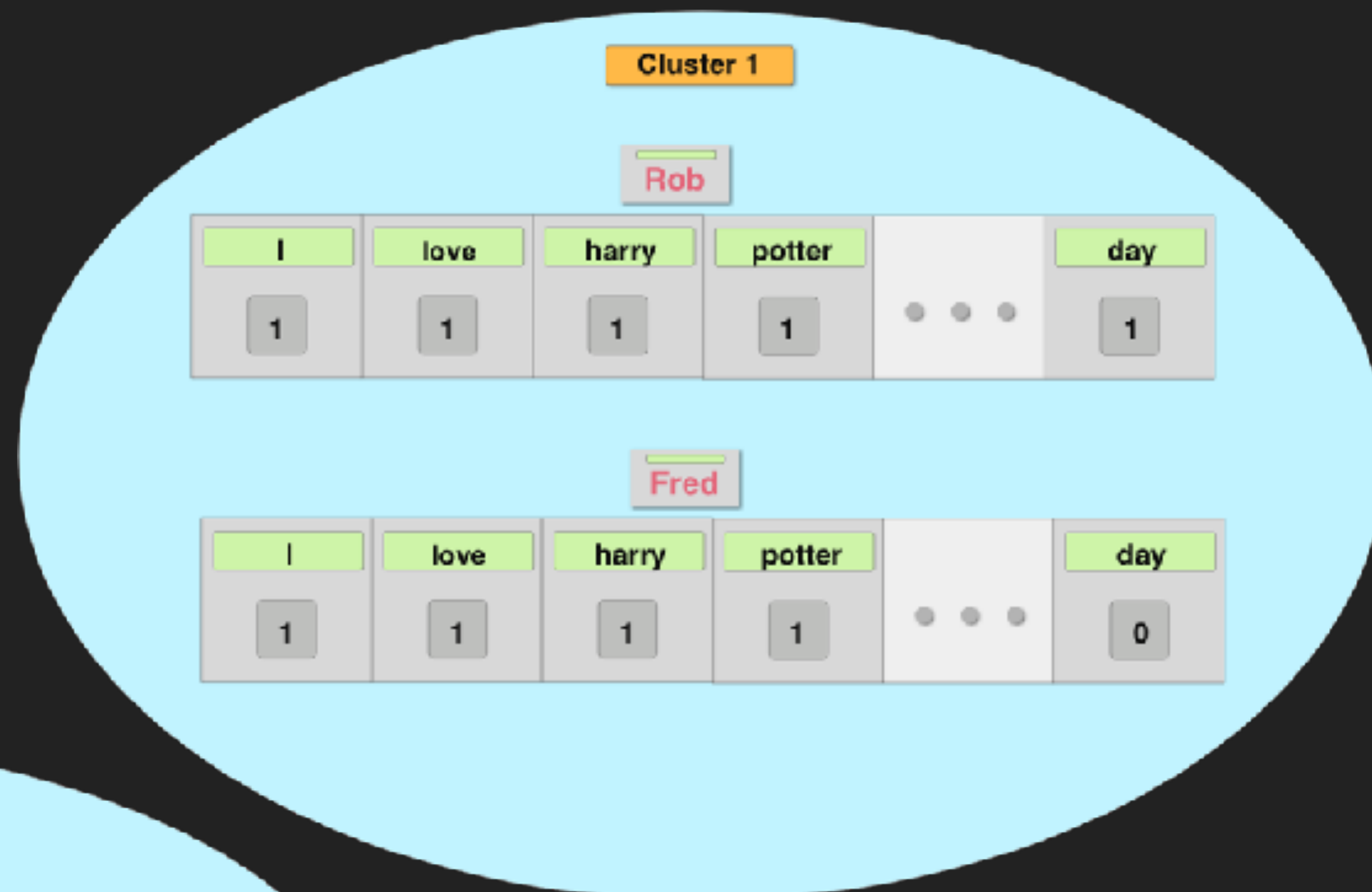
  - Bag of Words



METHODOLOGY - UTILITY LOSS FROM DISTORTION EXAMPLE

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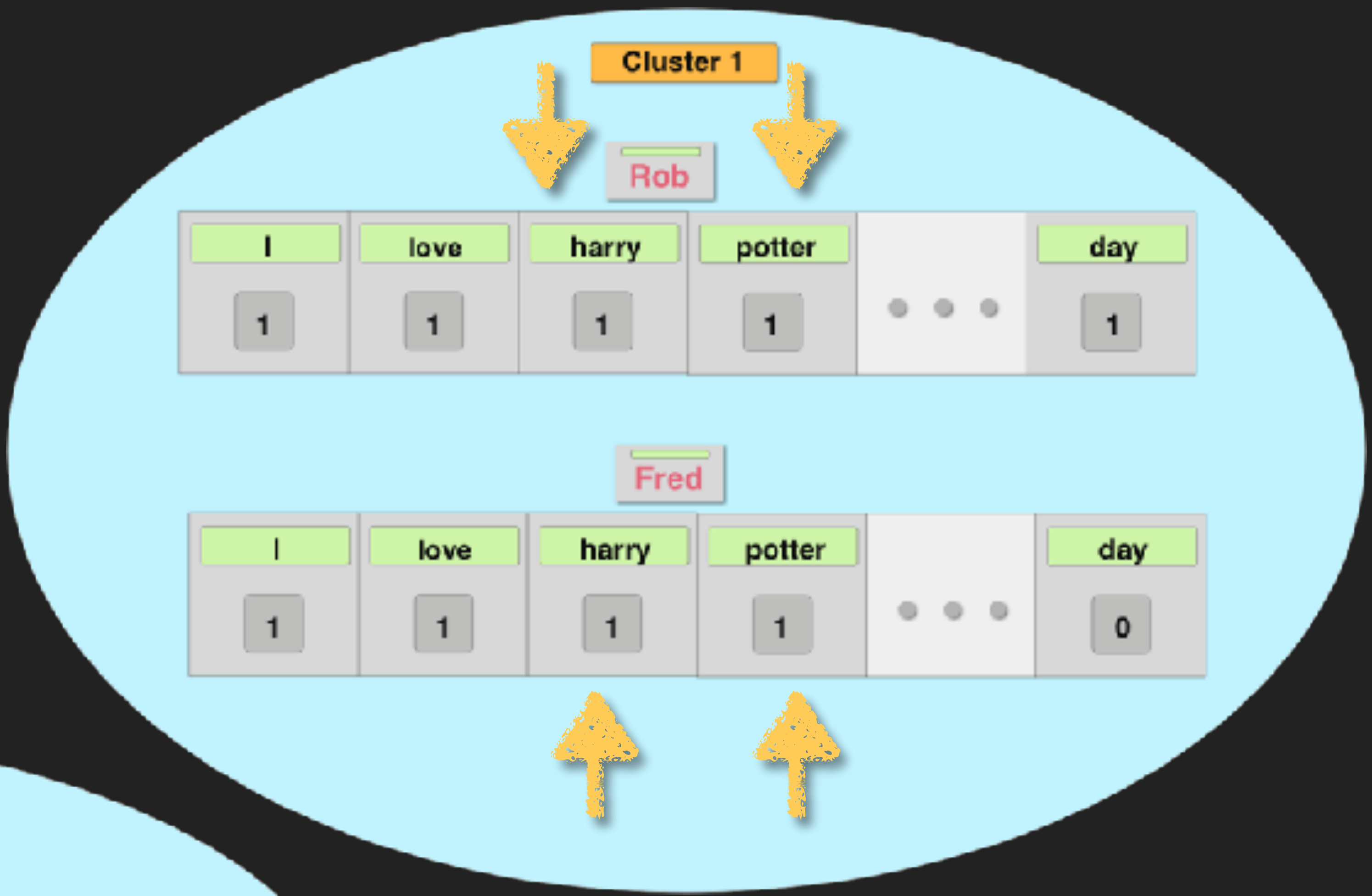
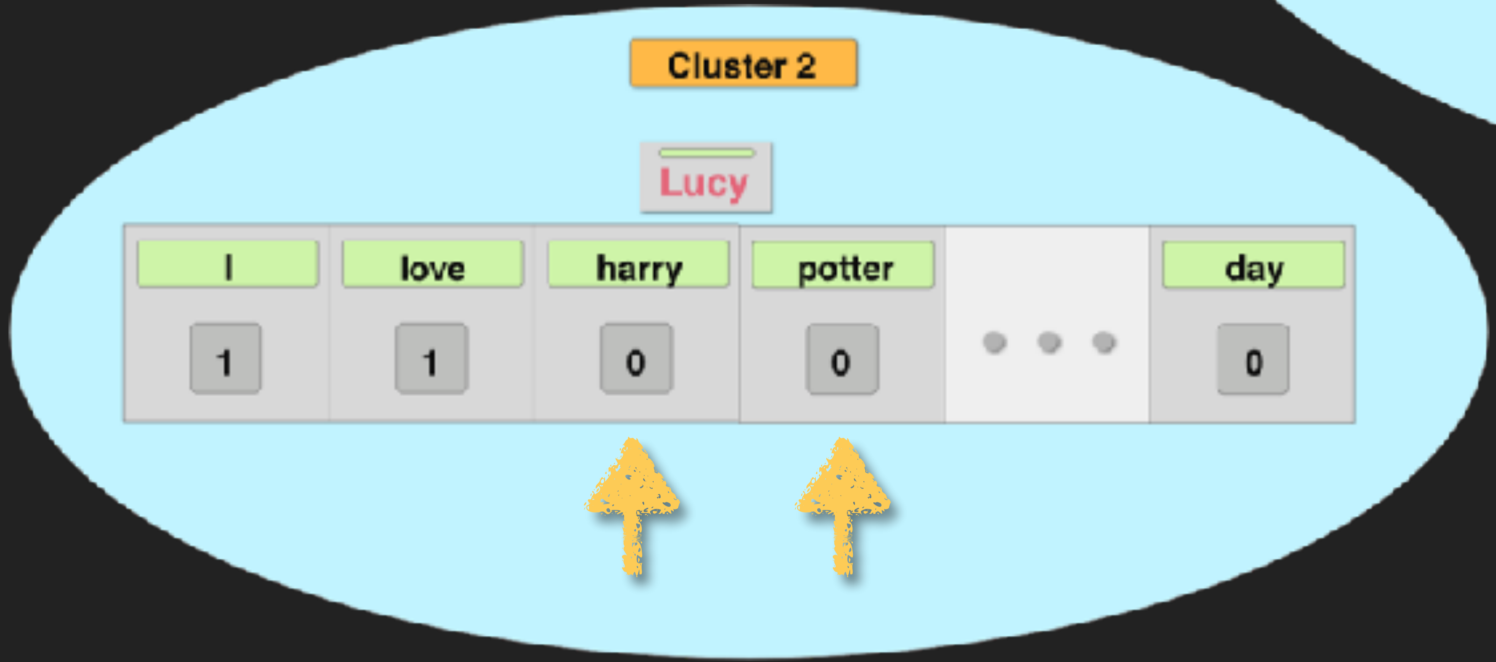
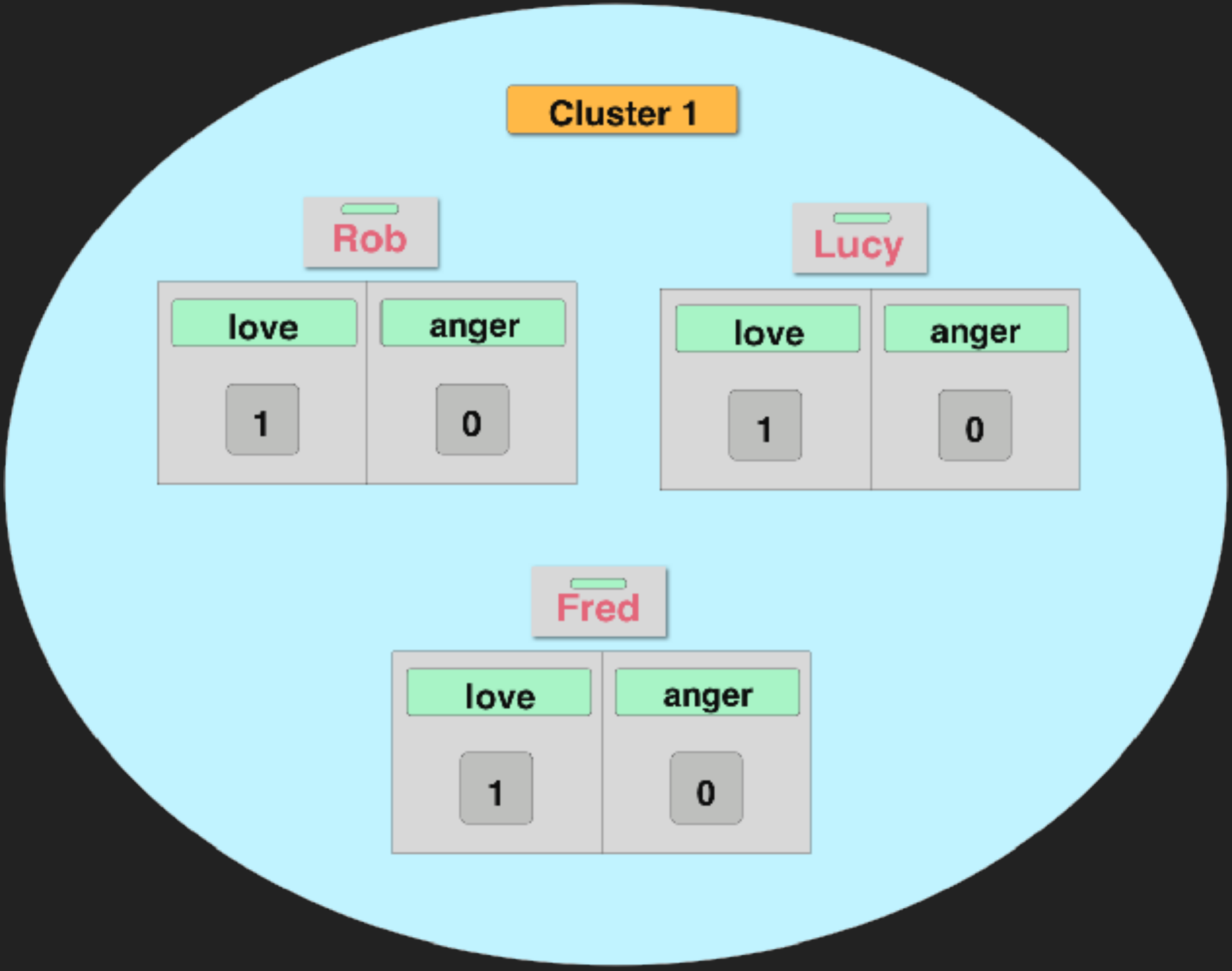




METHODOLOGY - UTILITY LOSS FROM DISTORTION EXAMPLE

- Clustering
  - Emotion Projection
  - Example of high distortion impacting utility



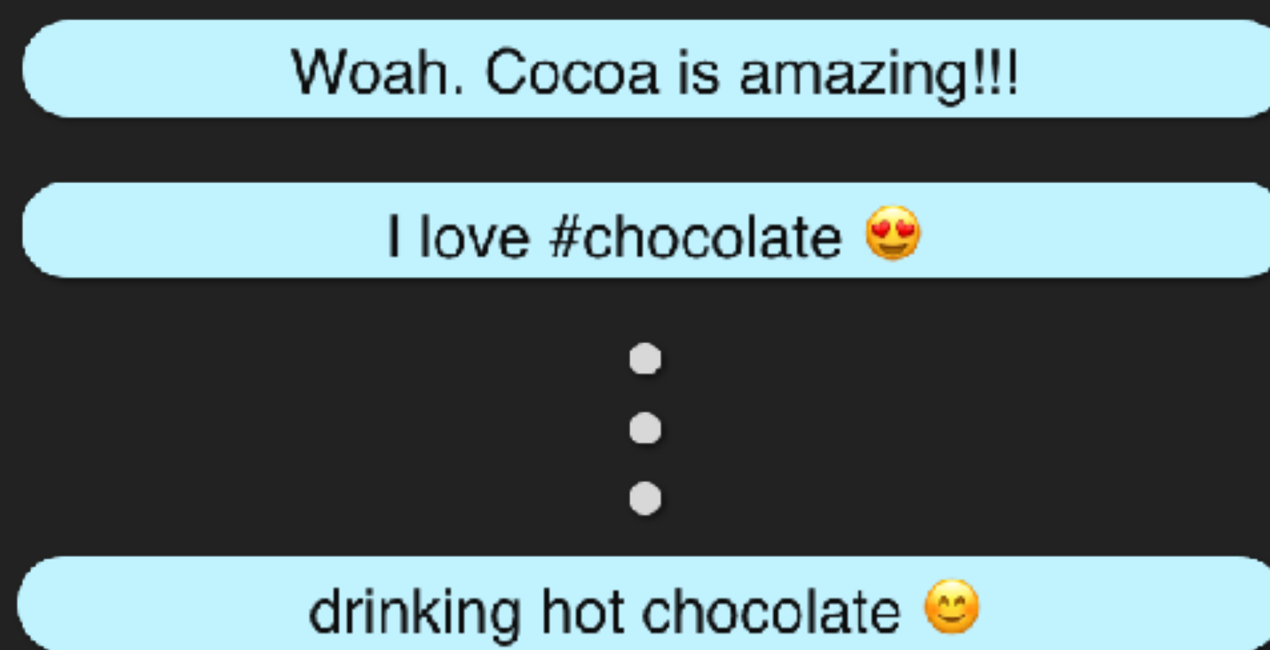
IDEAL DATA TRANSFORMATION

- High data utility
- Low individual distinguishability
- High distortion

CONTENT THAT MAY MATTER

- What makes an individual unique on Twitter?

1. Words used
    - punctuation use characteristics
    - feature Frequency
2. Substantive content discussed
3. Expressed emotionality
    - words & emoji
4. Engagement level



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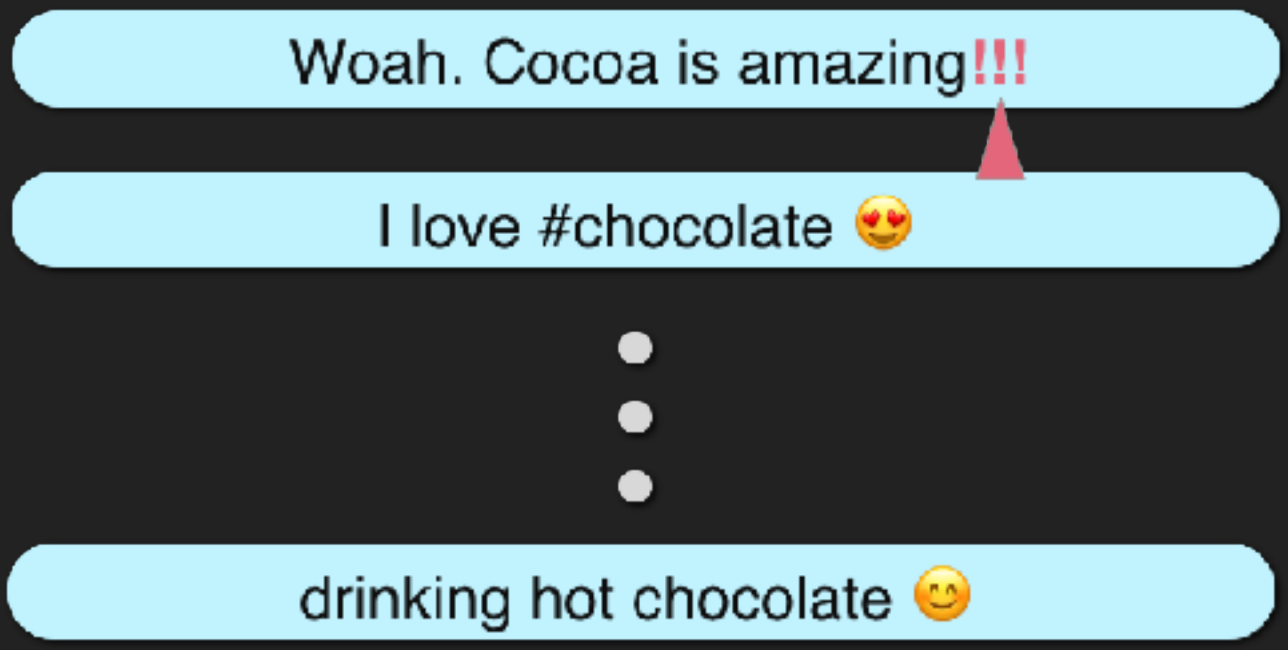

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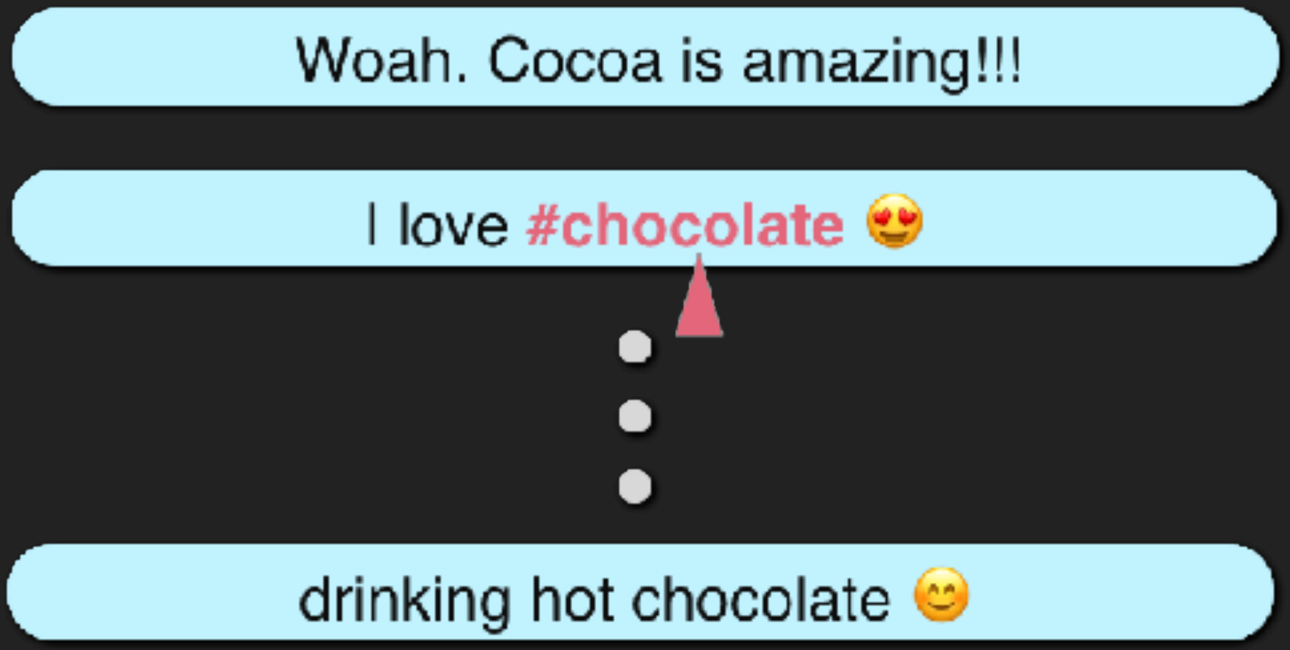

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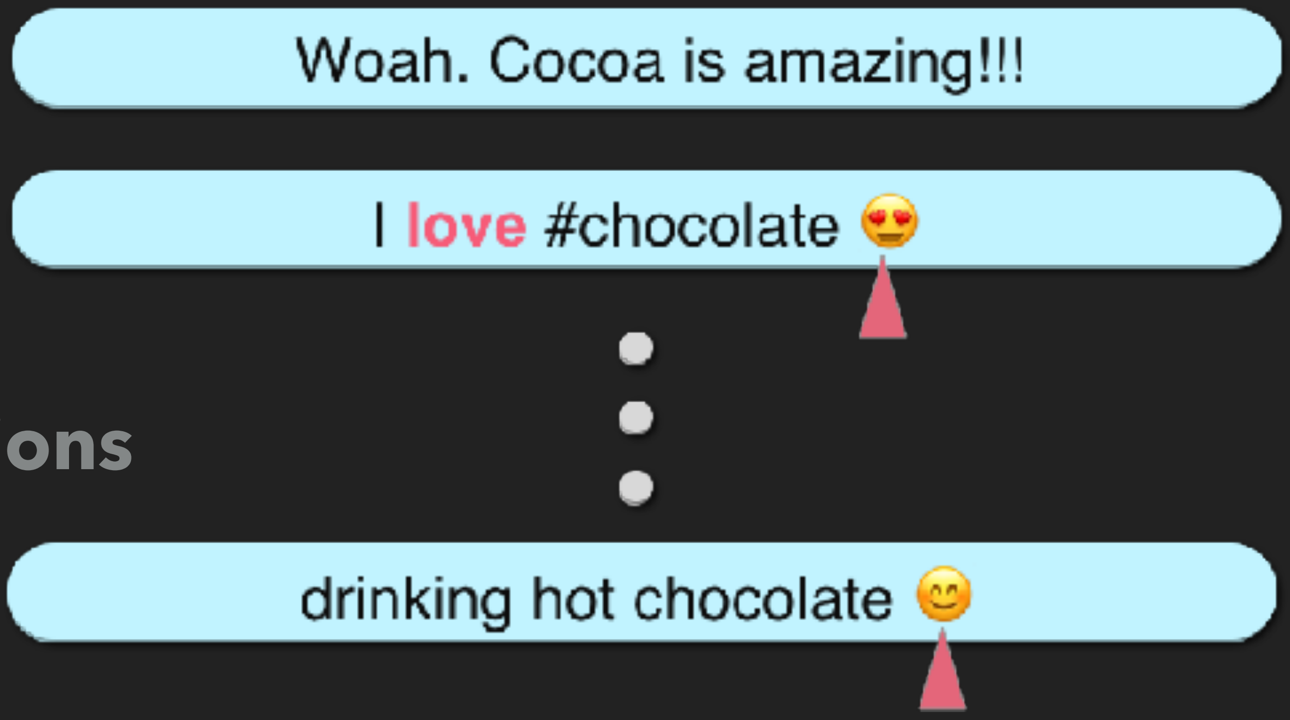
3. **Expressed emotionality**
    - **words & emoji & ascii expressions**
4. Engagement level



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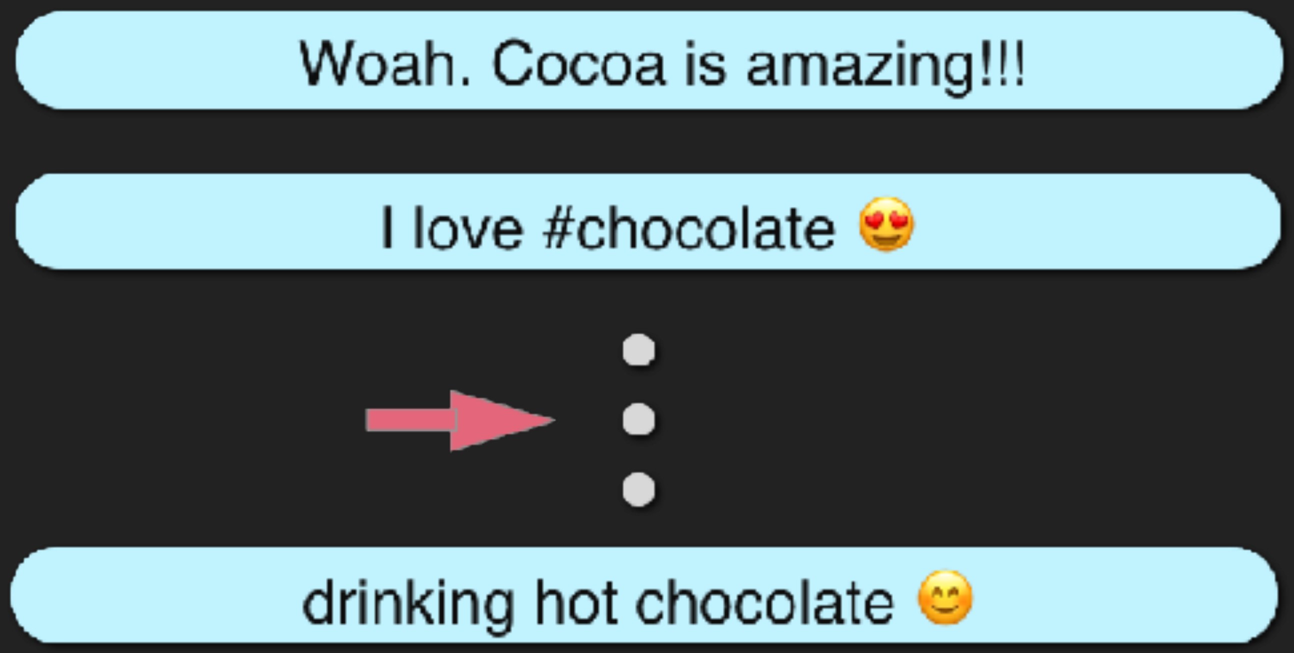
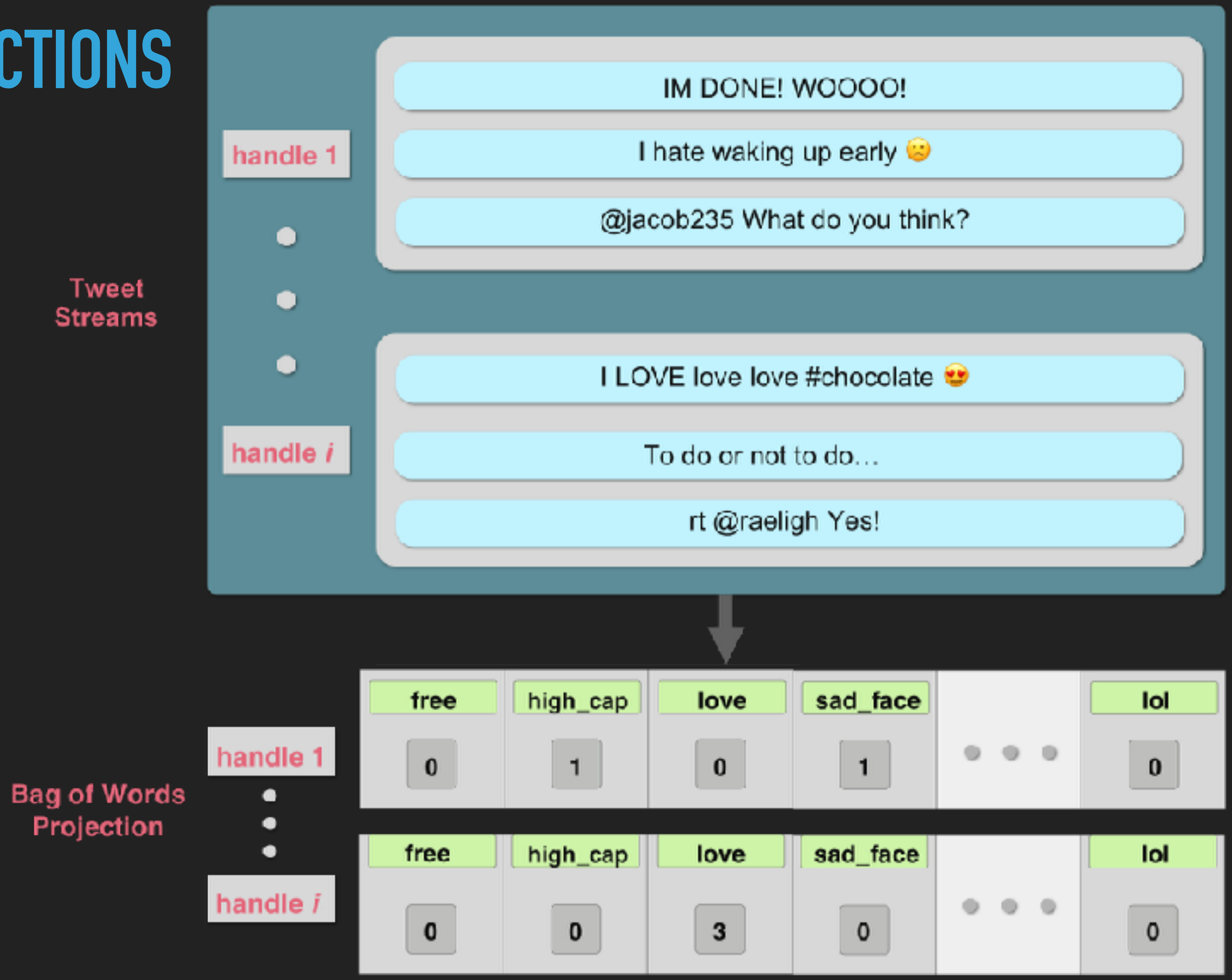


PROJECTIONS



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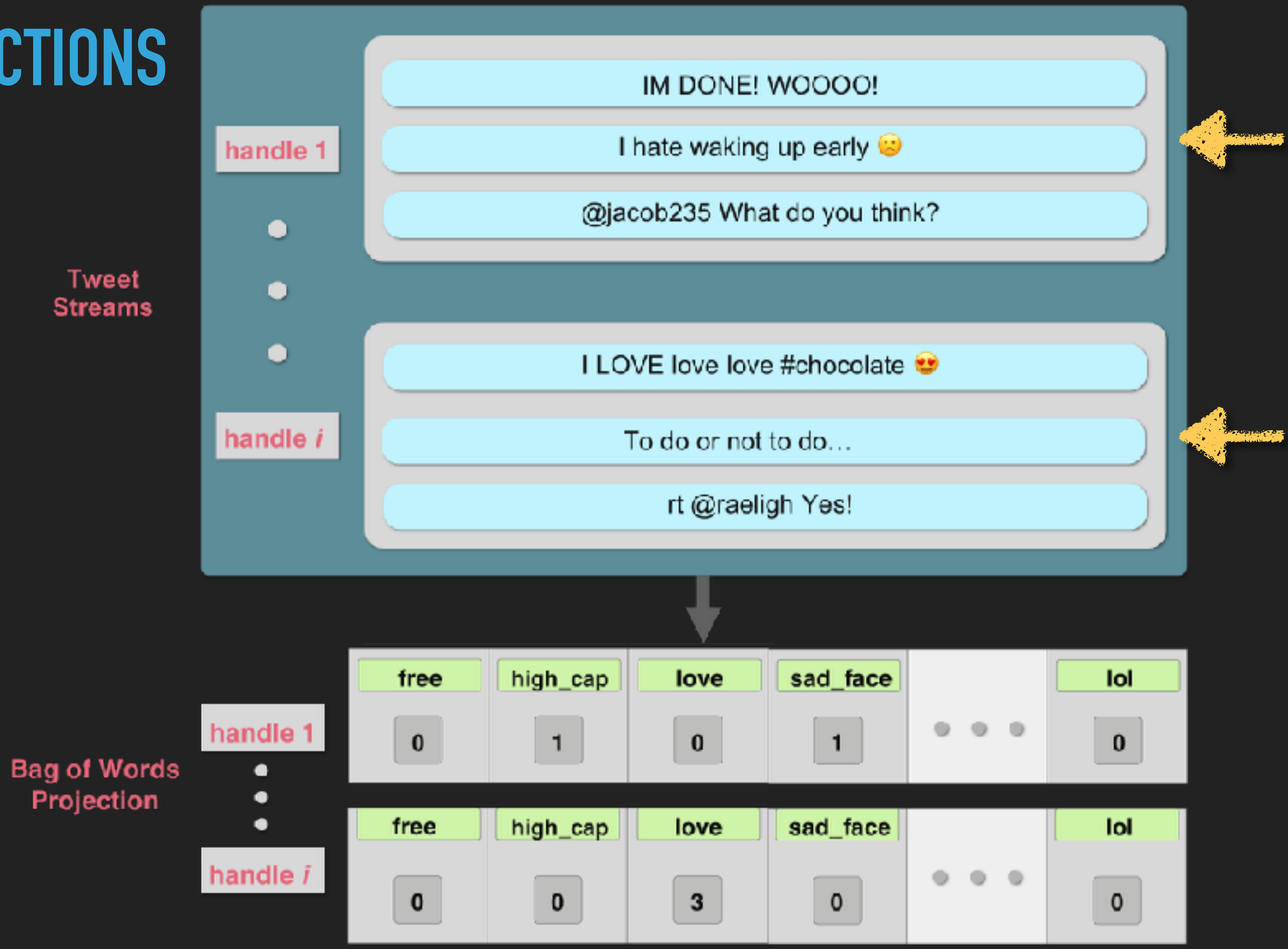

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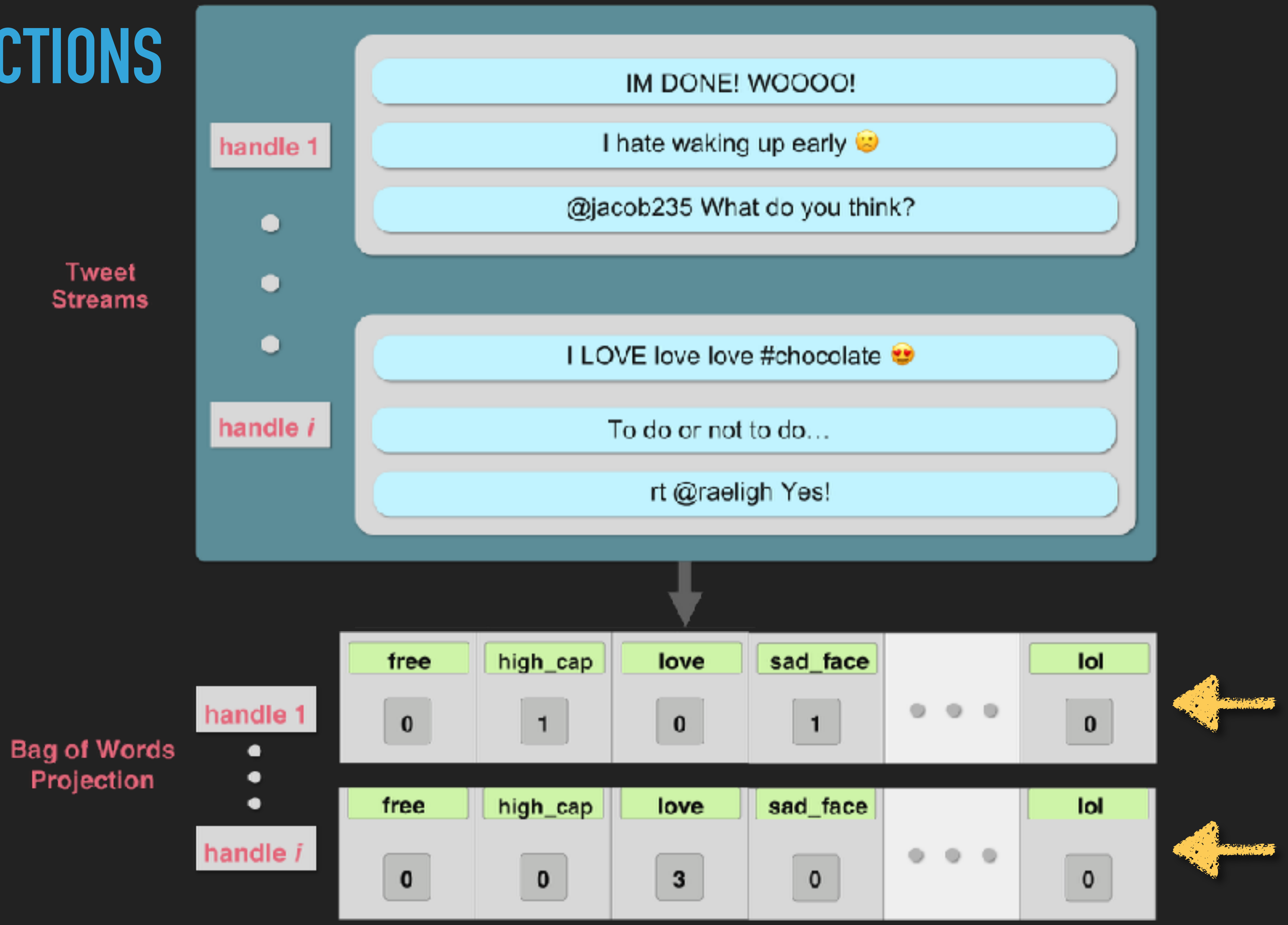

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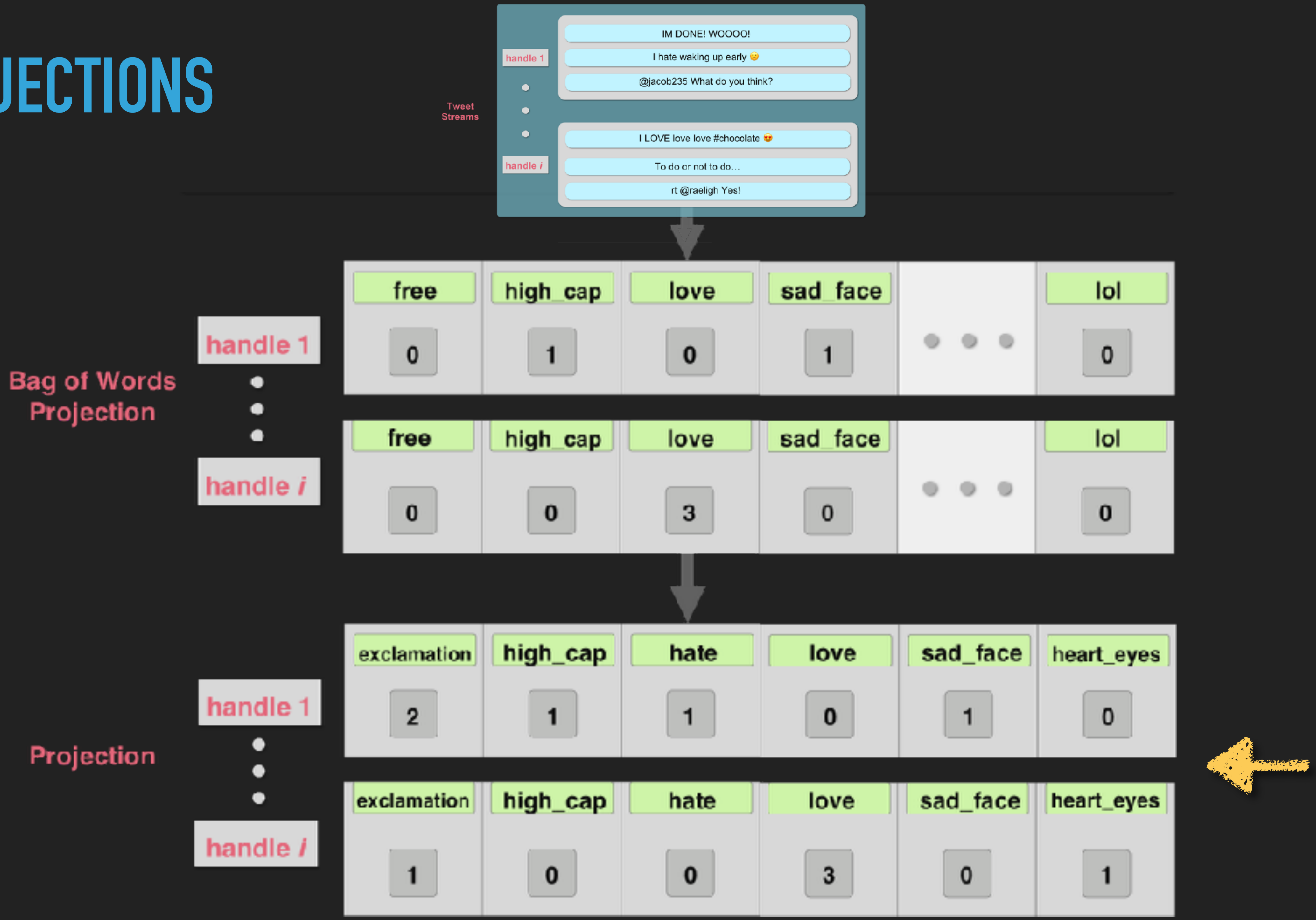
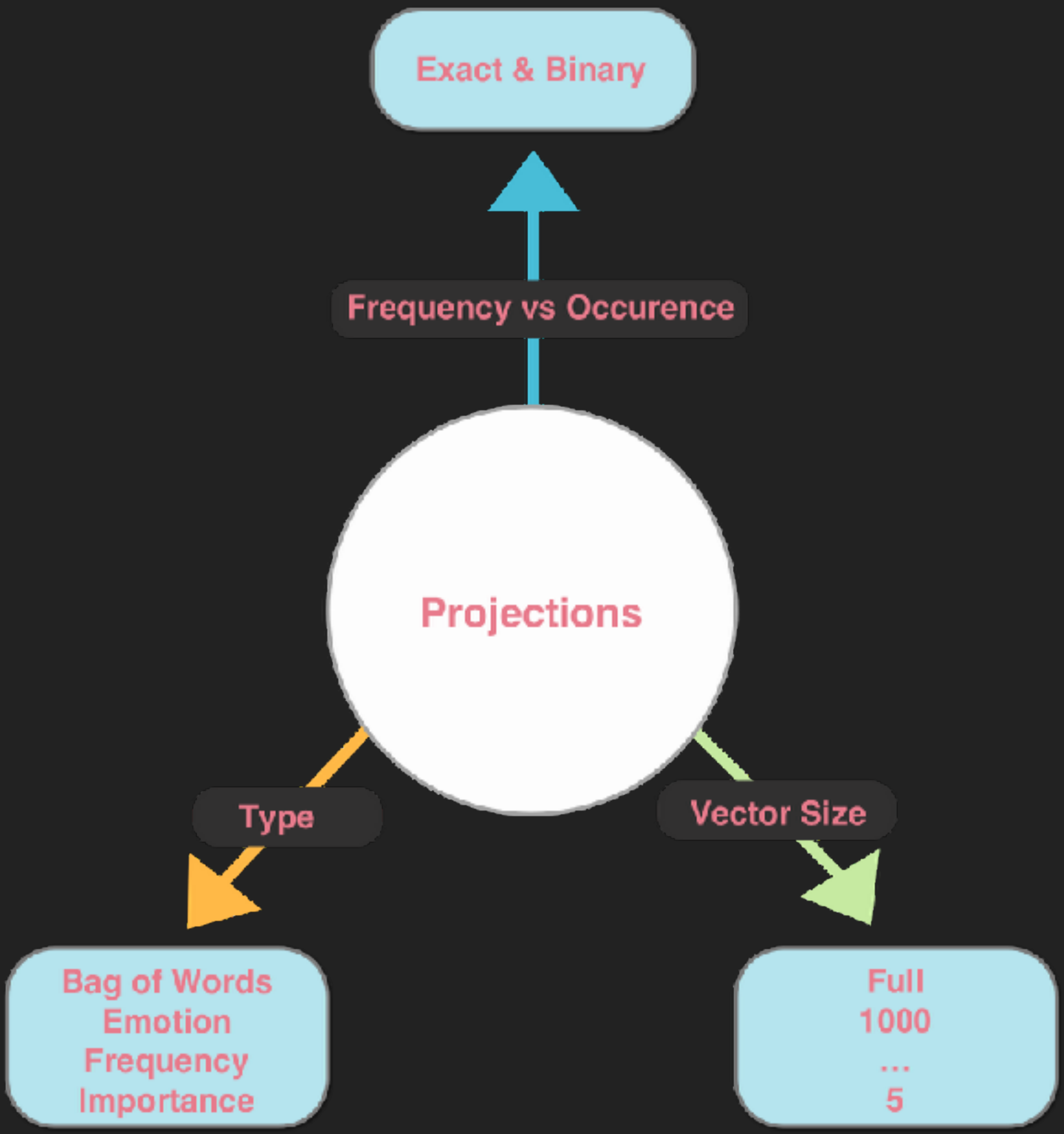


METHODS: PROJECTIONS

- We consider projections across three dimensions:
  - Projection type
  - Binary and exact
  - Projection length



METHODS: PROJECTIONS

- Emotion
- Frequency
- Importance

METHODS: PROJECTION CONSTRUCTION

Twitter Handle
FunSpanishTchr

tweet1
[tweet_num=20]

RT @Hlenggy_H: #ItsTimeIConfess I'm afraid to sit at the front seat of a taxi! 😶😢

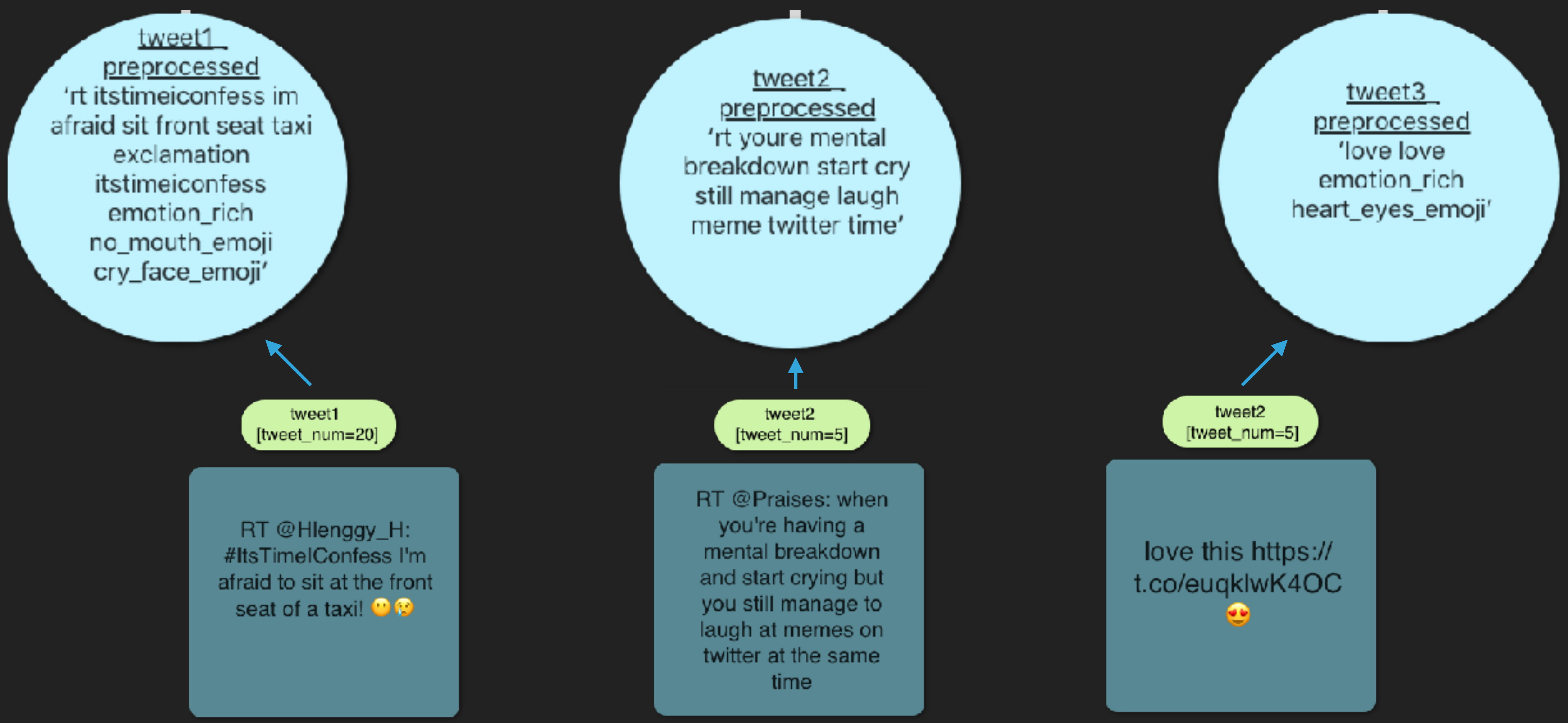
tweet2
[tweet_num=5]

RT @Praises: when you're having a mental breakdown and start crying but you still manage to laugh at memes on twitter at the same time

tweet2
[tweet_num=5]

love this https://t.co/euqklwK4OC 😍

METHODS: EMOTION PROJECTION



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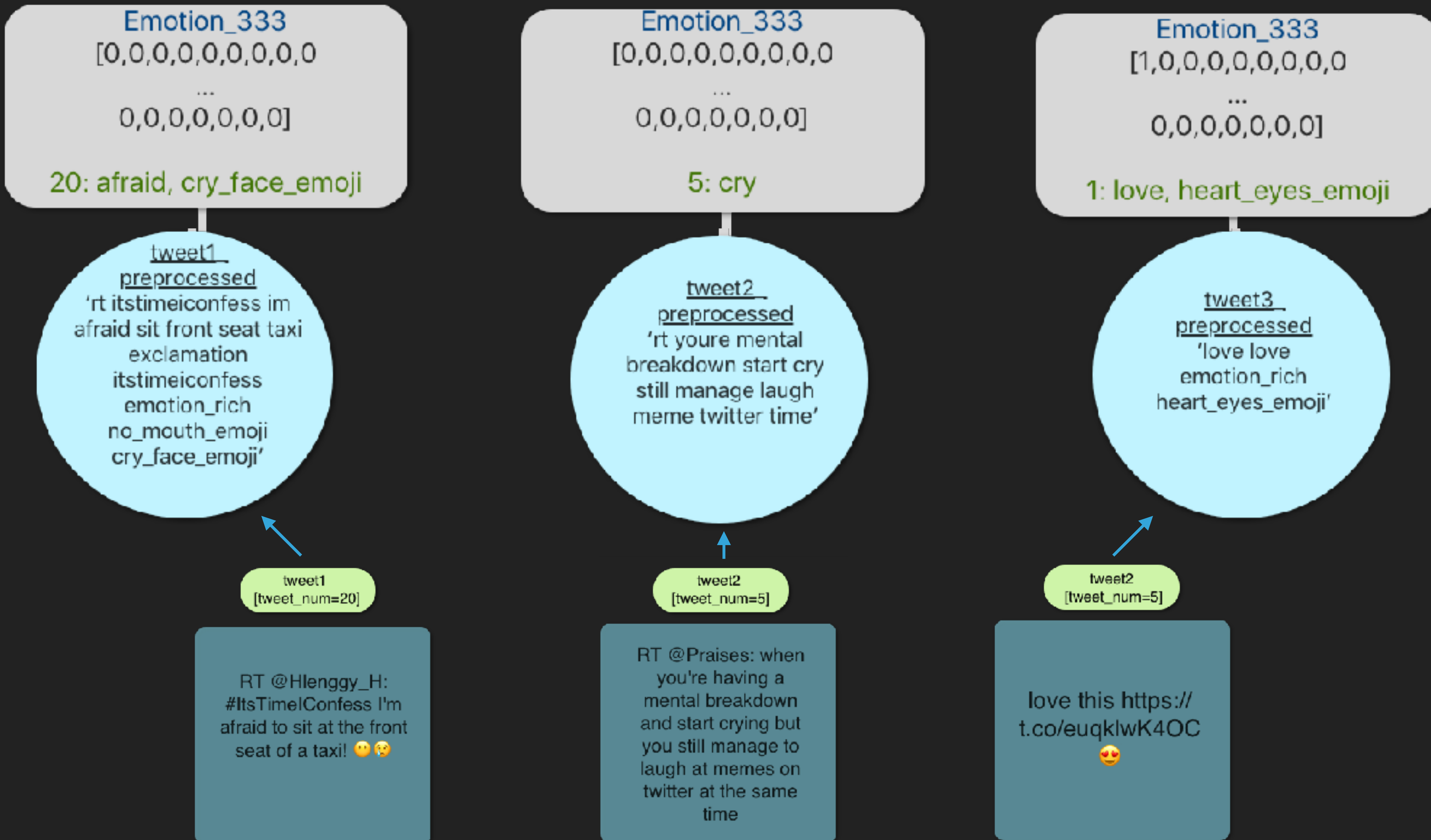

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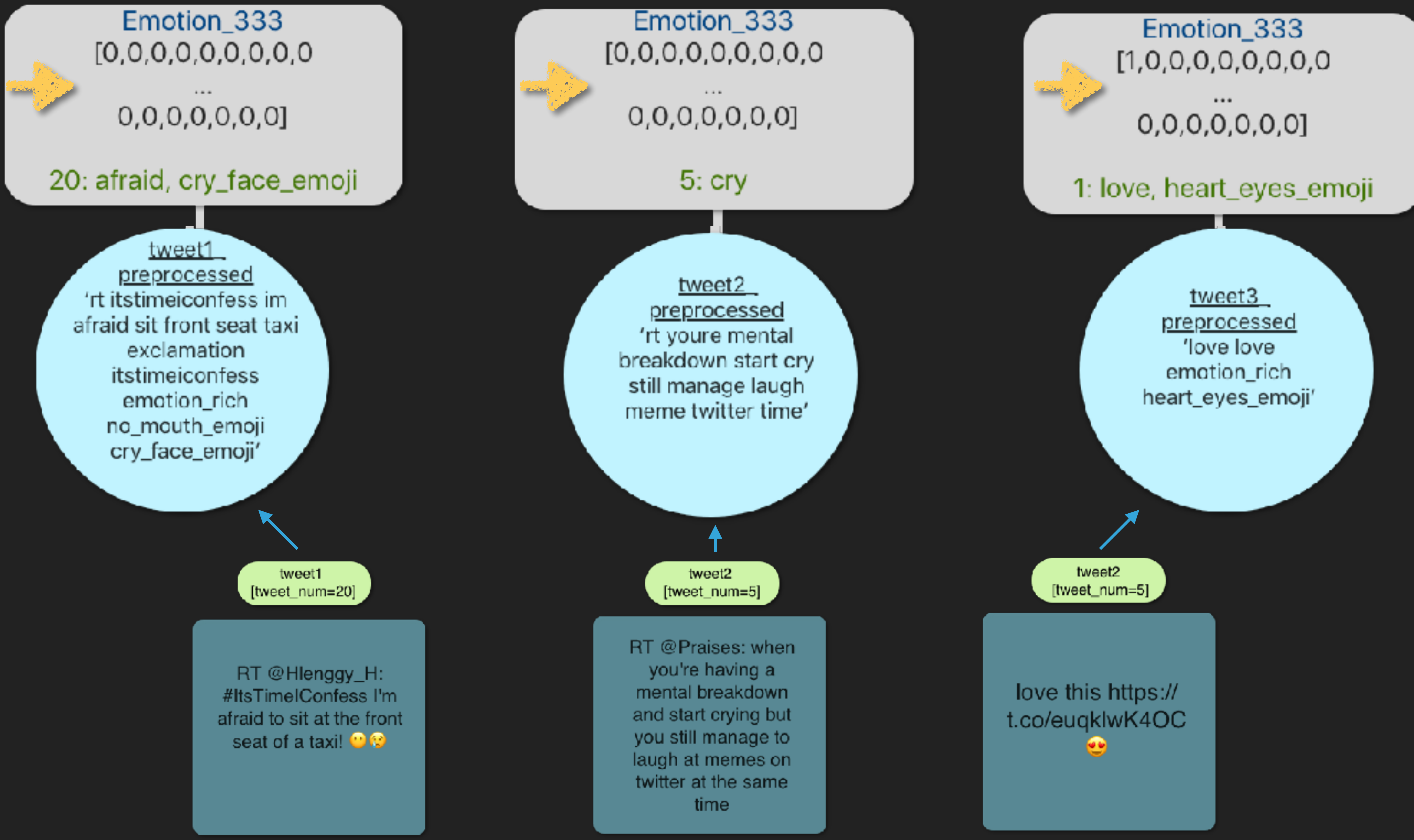

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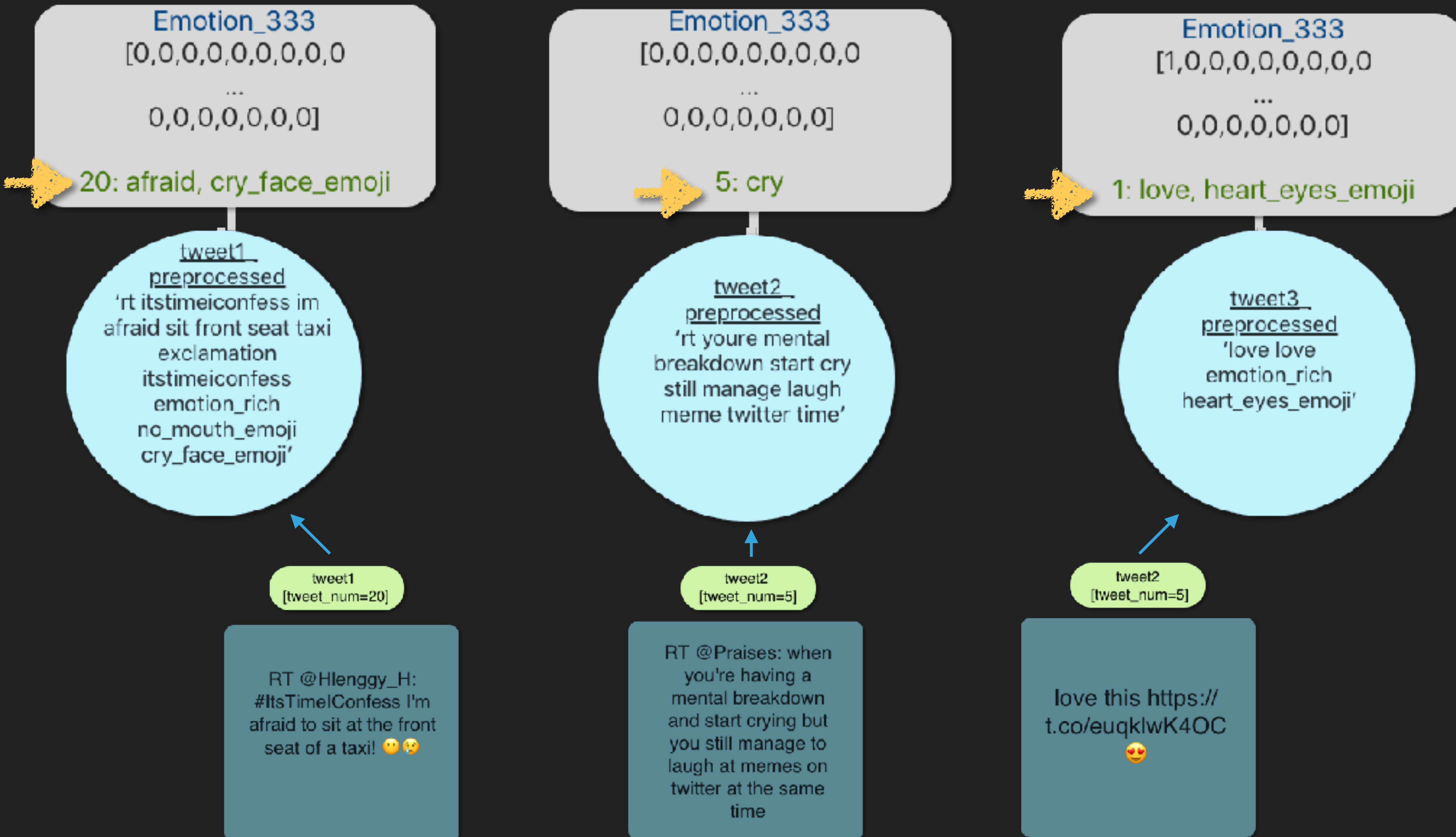
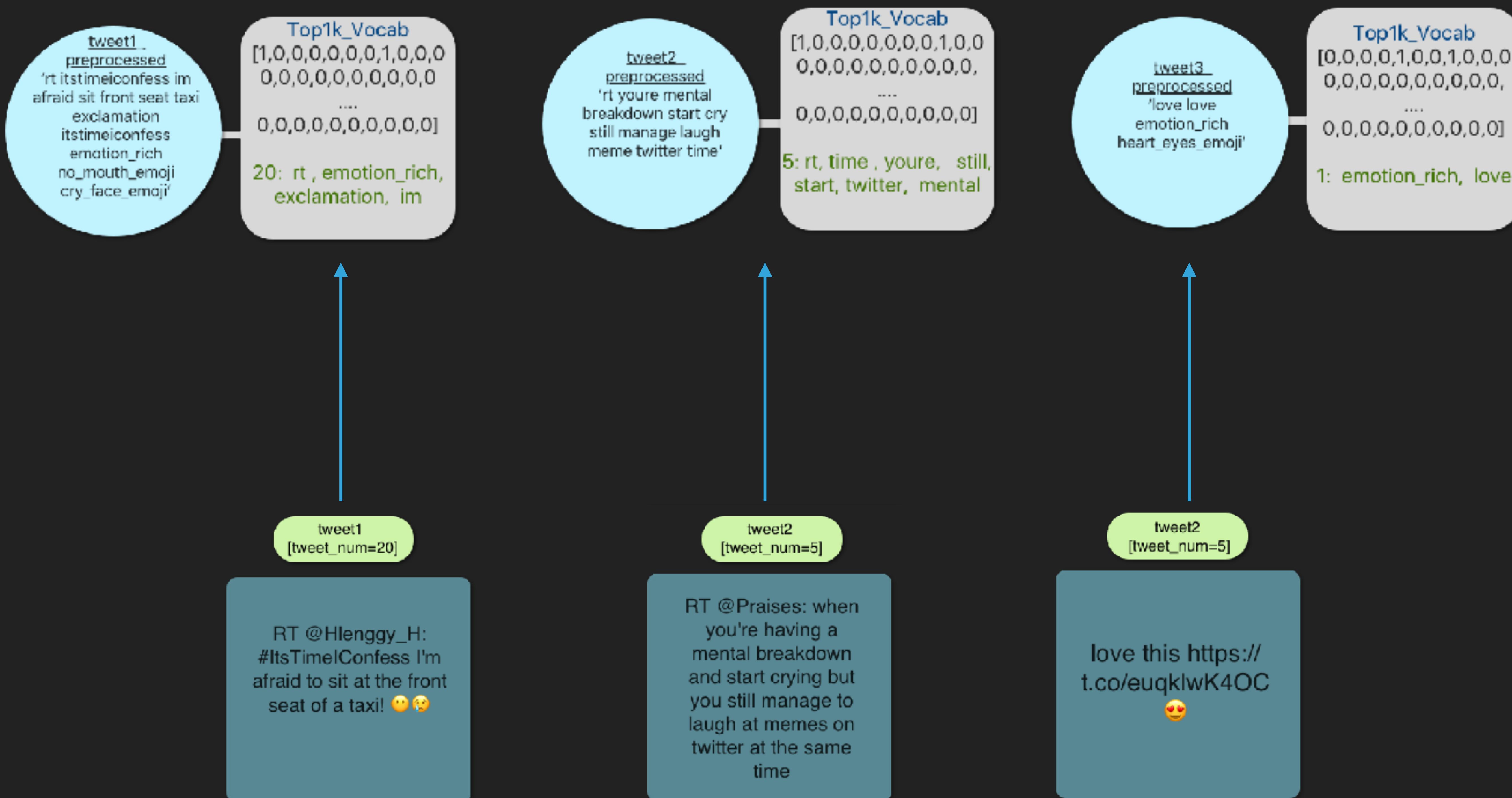


METHODS: FREQUENCY PROJECTION



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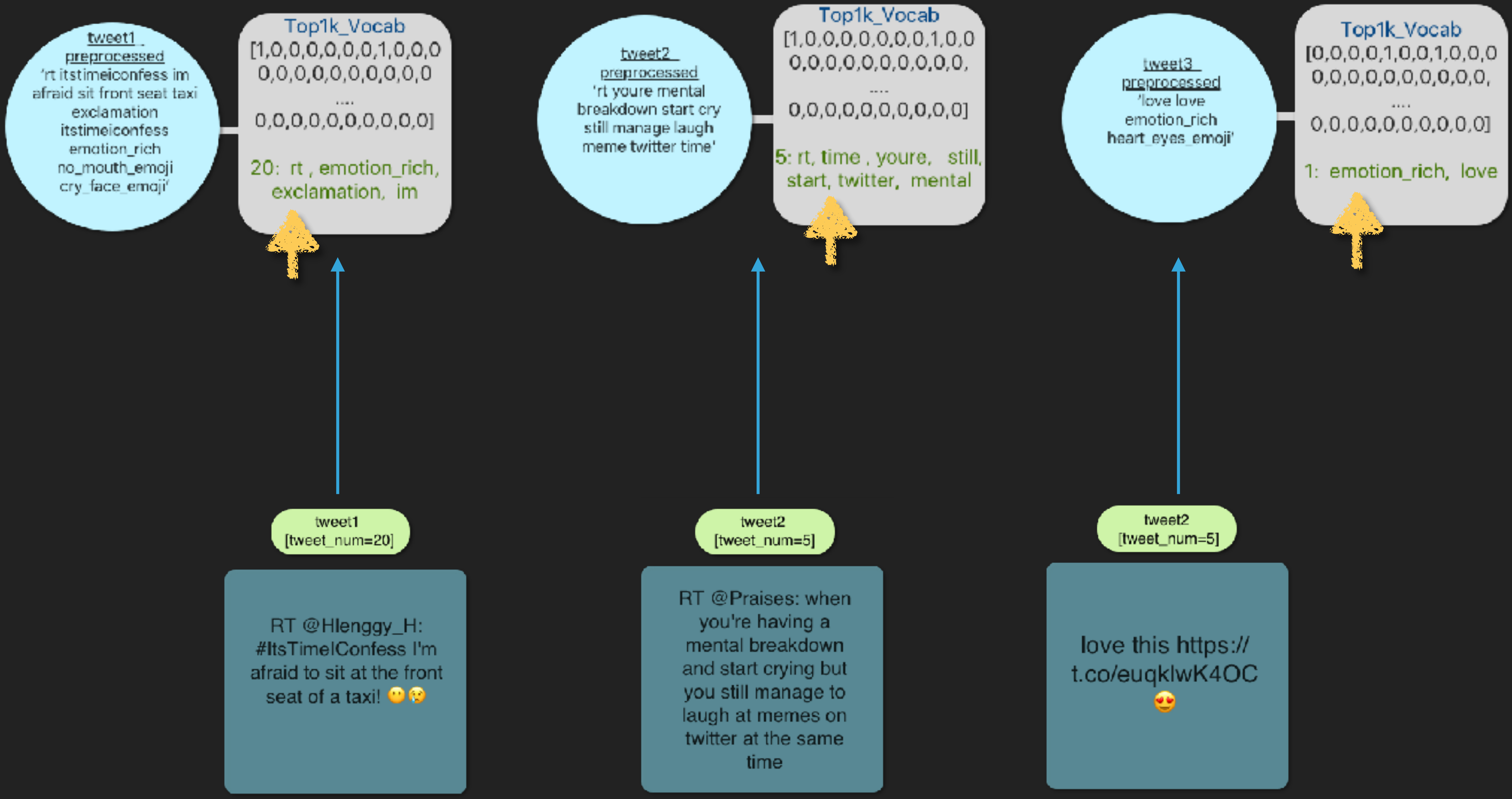

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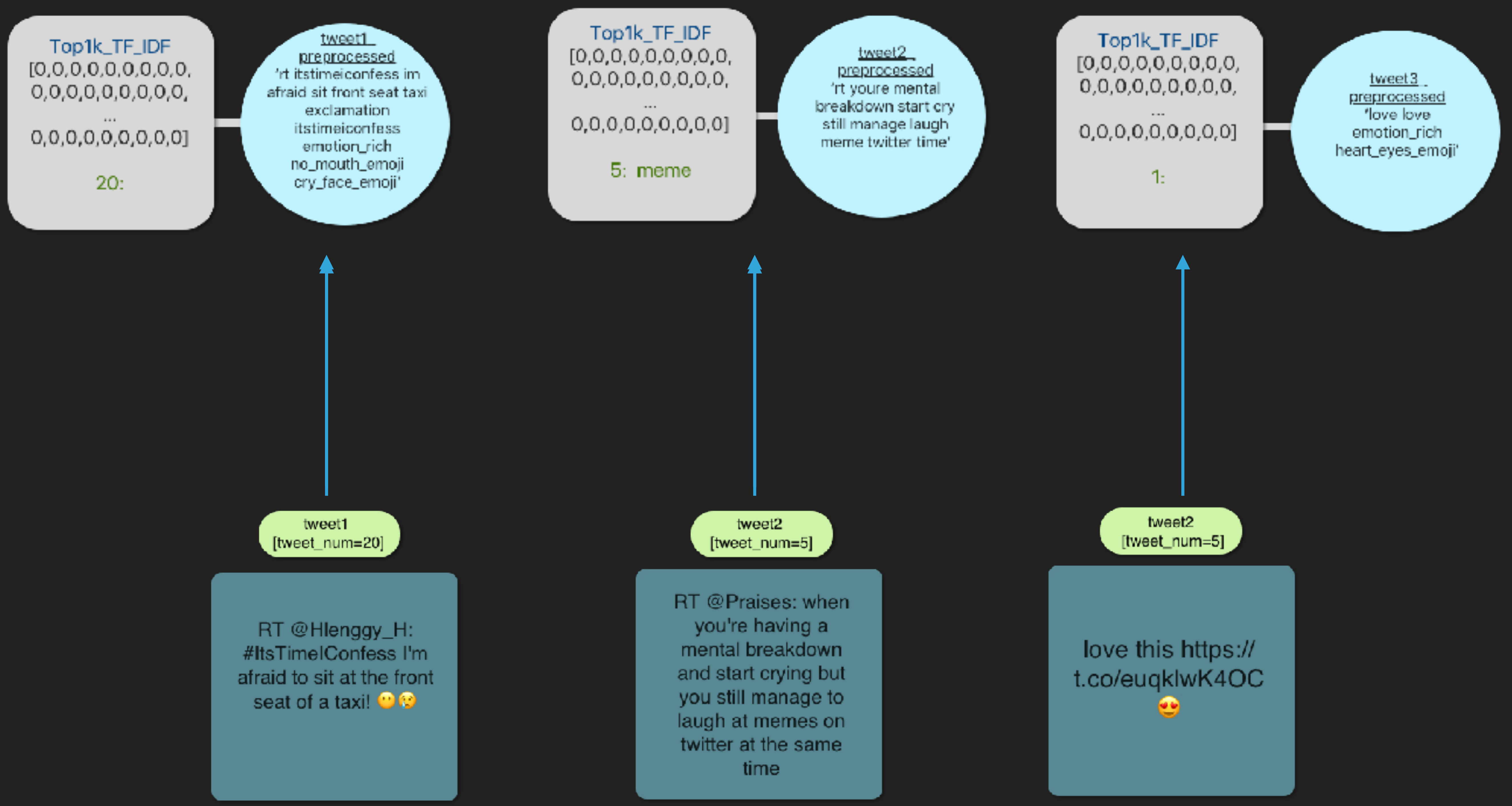

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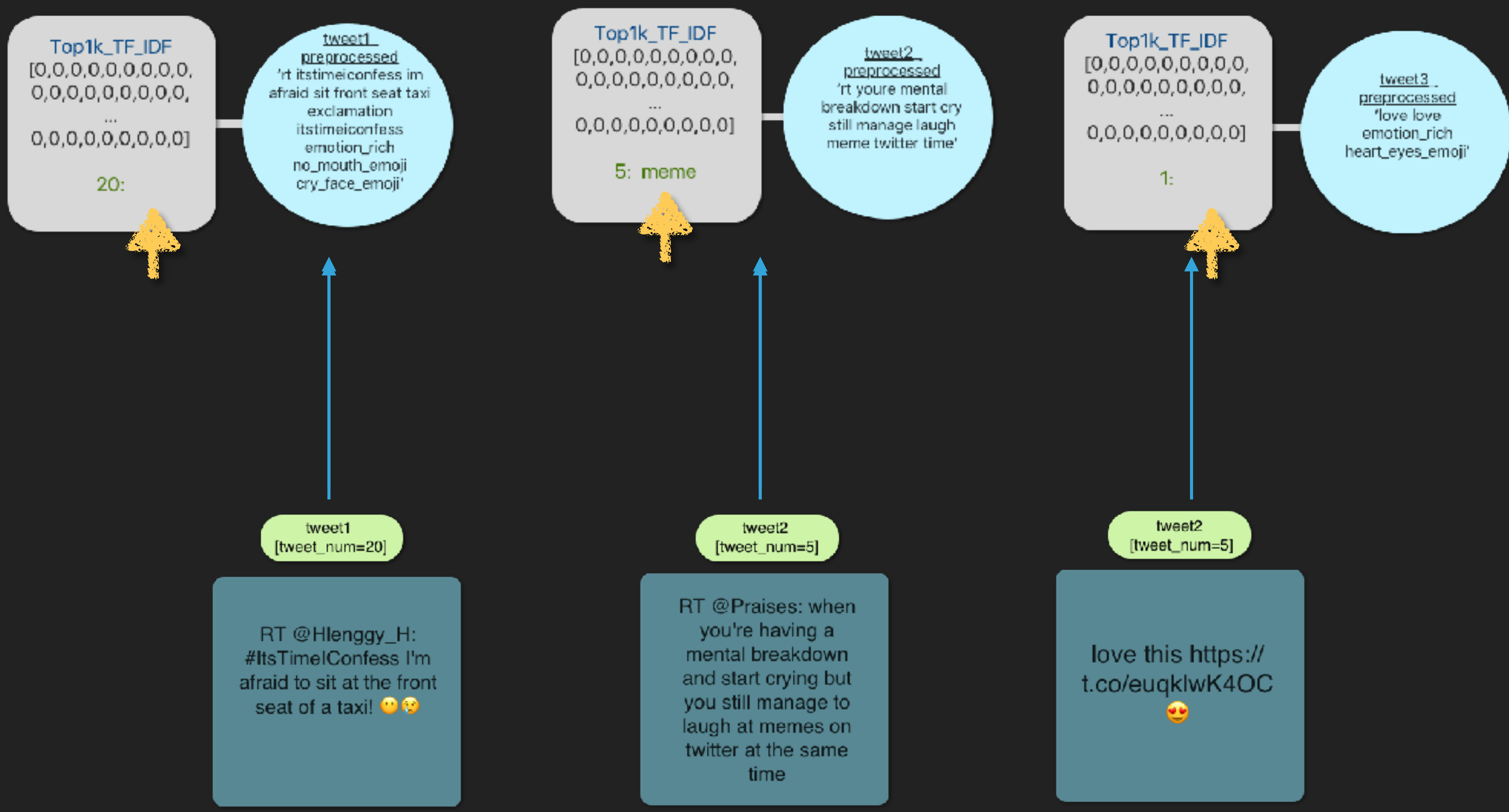

METHODS: PRIVACY METRIC

- k-anonymous vector privacy measure
- Measure of privacy for least private individual for a projection

METHODS: PRIVACY METRIC - EXAMPLE

- k-anonymous vector privacy measure
- Measure of privacy for least private individual for a projection

Same

exclamation	high_cap	hate	love	sad_face	heart_eyes
2	1	1	0	1	0

exclamation	high_cap	hate	love	sad_face	heart_eyes
2	1	1	0	1	0

METHODS: PRIVACY METRIC - EXAMPLE

- k-anonymous vector privacy measure
- Measure of privacy for least private individual for a projection

Unique

exclamation	high_cap	hate	love	sad_face	heart_eyes
5	1	1	1	3	1

exclamation	high_cap	hate	love	sad_face	heart_eyes
2	1	1	0	1	0

METHODS: PRIVACY METRIC – EXAMPLE

- k-anonymous vector privacy measure
- Measure of privacy for least private individual for a projection

All-zero

- Often private, but no data utility

METHODS: UTILITY RETENTION METRICS

- Clustering
- Anomaly Detection
- Frequent Item Set Mining

METHODS: UTILITY RETENTION METRICS - CLUSTERING TASK

- Utility Retention Metric
  - Proportion of cluster labels shared between projection and baseline (Bag of Words)

METHODS: UTILITY RETENTION METRICS - ANOMALY DETECTION TASK

- Utility Retention Metric
  - Kendall Tau rank correlation coefficient [Kendall, 1938]
    - Measure of ordinal association between two measured quantities

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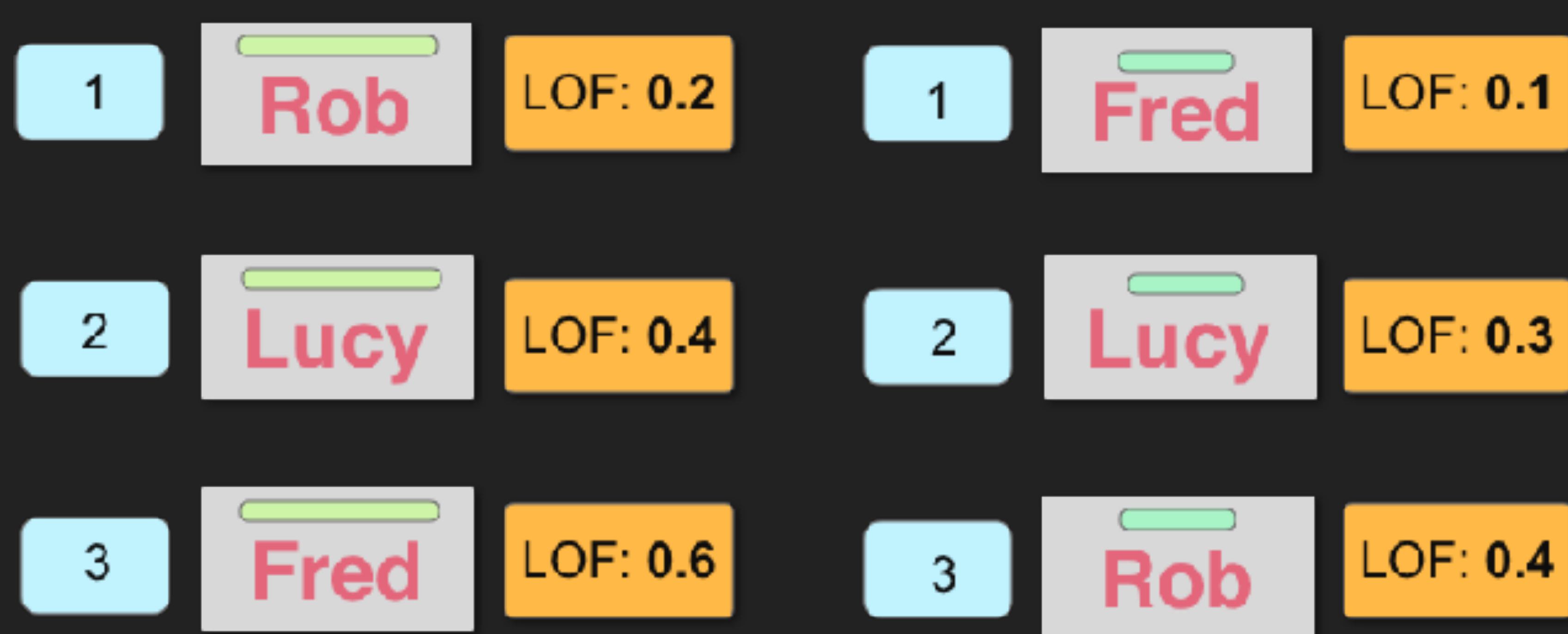

METHODS: UTILITY RETENTION METRICS – FREQUENT ITEM SET MINING TASK

- Utility Retention Metric
  - Average of (i) proportion of items sets from projection also in Bag of Words item sets [precision] and (ii) proportion of Bag of words item sets in item sets of projection [recall]

METHODS: DISTORTION METRICS

- Proportion of features lost for each handle
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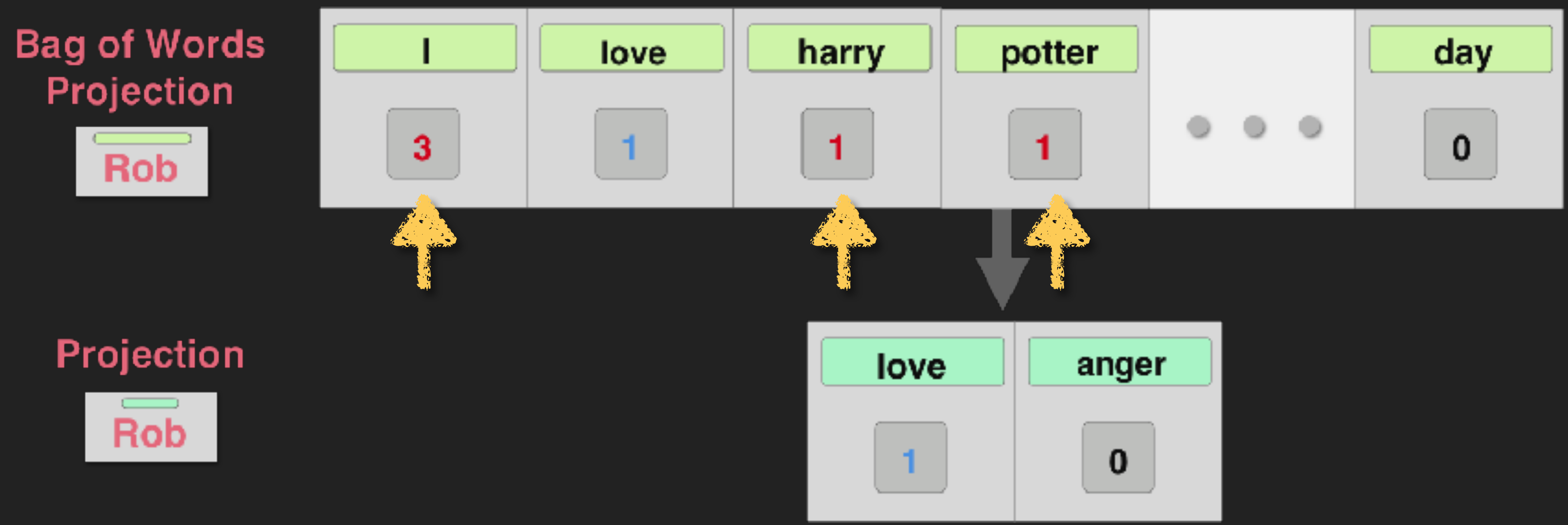

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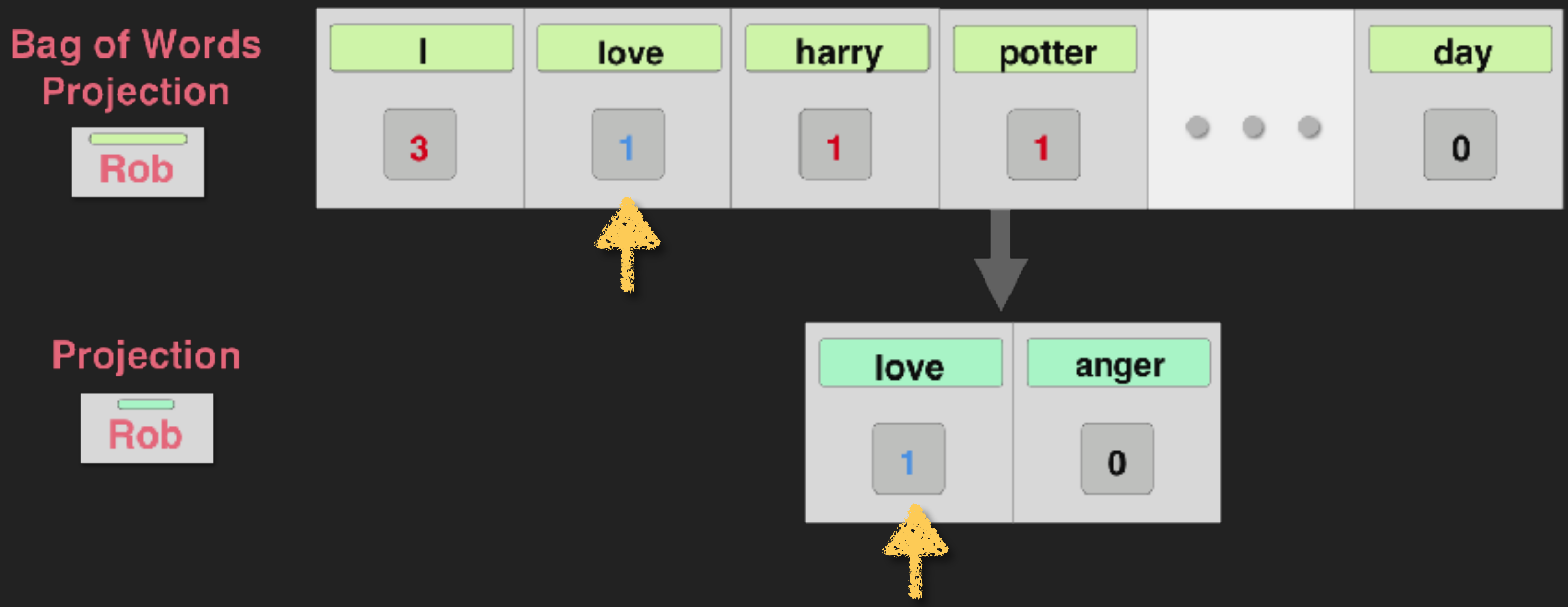
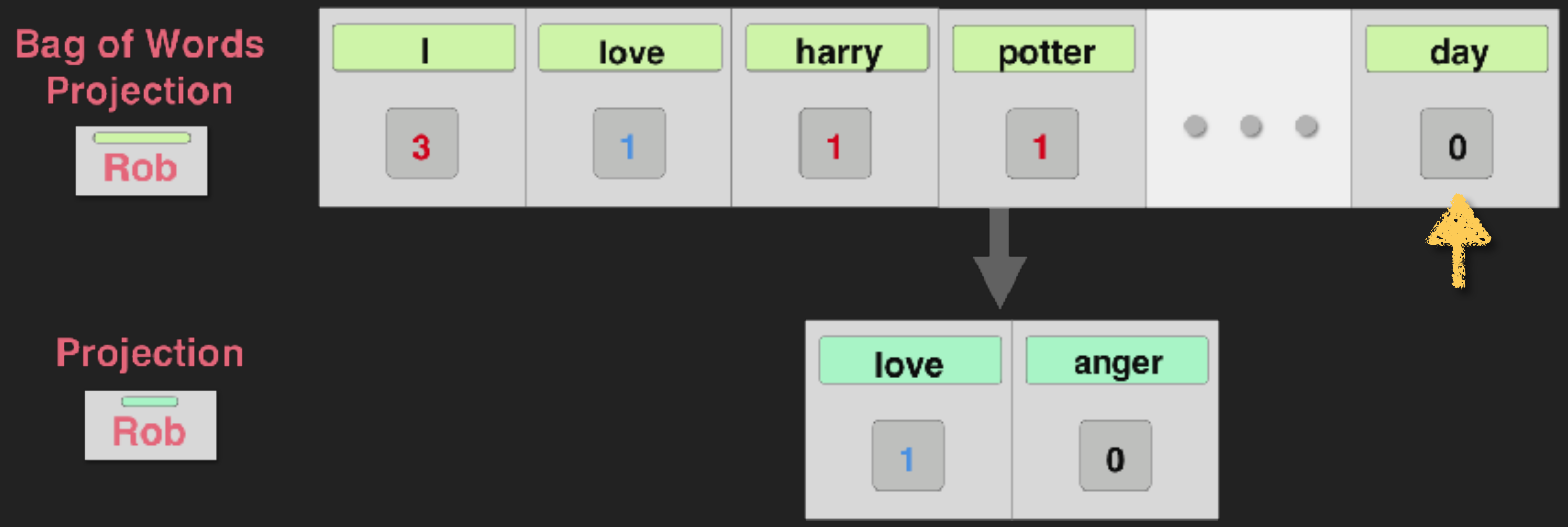
- Do not count zero-valued features
  - No distinguishing features lost



METHODS: DISTORTION METRICS

- Proportion of features lost for each handle
- Do not count zero-valued features
  - No distinguishing features lost



ENGAGEMENT LEVELS

- High
  - 2000 < number of tweets
- Moderate
  - 200 < number of tweets <= 2000
- Low
  - 20 <= number of tweets <= 200

DATA DESCRIPTION

TWEET COLLECTION

- 110,891 Twitter handles
  - 10 main handles, 9 corresponding to parenting and 1 to medical sites
  - ~10,000 handles following each of these main handles
- Active Collection
  - mid 2016 - end of 2017
  - Most recent 3500 tweets for each handle collected at commencement
    - Tweets may be missed in the case of high engagement

DATA SET

- Goal: ~1000 handles for each engagement level
- 5626 handles of those obtained in tweet collection
- 4 million tweets

EXPERIMENTS & RESULTS

PREPROCESSING OF DATA

- Lemmatization
  - to reduce noise
- Feature Injection
- Cleaning

PREPROCESSING OF DATA - FEATURE INJECTION

- Emoji and ascii expressions
  - Normalization
- Punctuation
  - Exclamation, extreme exclamation
- Emotional richness
- High capitalization

PREPROCESSING OF DATA - CLEANING

- Removal:
  - Hyper-links
  - Twitter handle references
  - All-number & all-punctuation words
  - Stop words
- Fix contractions
- Case lowering

COMPUTATION OF DATA PROJECTIONS - BAG OF WORDS

- 767,937 features
  - 256,135 features are hapax legomenon
- 47 all-zero vector representations of handles' tweet streams
  - Few tweets
  - No features left after removal of handle references, urls, & stop words
- Baseline projection

COMPUTATION OF DATA PROJECTIONS - EMOTION

- 333 features for the following emotional categories
  - anger_disgust
  - fear
  - joy_love
  - sadness
  - surprise
- Features include emoji & ascii expressions

COMPUTATION OF DATA PROJECTIONS - EMOTION

- Features selected by
  - Human selection of fundamental synonyms for the five emotional categories
  - High occurrence of a word in tweets classified as expressing one of the five emotional categories
    - Used Emotional Lexicon Hit Method
      - Average precision 0.551, average recall 0.662
      - Tried Naïve Bayes and SVMs as well, but Emotional Lexicon Hit Method had best performance on average
    - 600 labeled tweets

COMPUTATION OF DATA PROJECTIONS – EMOTION

- Example synonyms:

anger_disgust	fear	surprise	sadness	joy_love
anger	fear	surprise	sadness	joy
disgust	fright	amazed	sad	love
sickening	frightened	astonished	dispirited	encouraged
outraged	panic	astounded	heartbroken	smiling
ew	worry	dumbfounded	morose	laugh
angry_pout_face	fearful_face	open_mouth_face	cry_face	grin_face
stream_from_nose_face	worried_face	surprise_face	frown_face	heart_emoji
...	...	...	...	...

COMPUTATION OF DATA PROJECTIONS - EMOTION

- Example synonyms:

anger_disgust	fear	surprise	sadness	joy_love
anger	fear	surprise	sadness	joy
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ew	worry	dumbfounded	morose	laugh
angry_pout_face	fearful_face	open_mouth_face	cry_face	grin_face
stream_from_nose_face	worried_face	surprise_face	frown_face	heart_emoji
...	...	...	...	...

COMPUTATION OF DATA PROJECTIONS – FREQUENCY

- Feature space:
  - 1,000 most frequently occurring words across set of tweet streams
- Potentially noisy projection

COMPUTATION OF DATA PROJECTIONS - IMPORTANCE

- Feature space:
  - 1,000 most important words across set of tweet streams
  - Determined by tf-idf measure [Jones, 1972]
    - Computed for each word, for each document (handle)
  - 94% of features are hashtag words
- Projection for substantive content (using hashtags as a proxy for topics)

COMPUTATION OF DATA PROJECTIONS - FEATURE SPACE REDUCTION

- Reduce feature space of projections to evaluate impact on privacy & utility
- Frequency & Importance projections
  - Use top *n* features to represent tweet streams
- Emotion Projection
  - Represent tweet streams according to our five emotional categories
  - Value of emotional category feature corresponds to number of observed synonym occurrences for that emotional category

COMPUTATION OF UTILITY - K MEANS

- To determine value for k, conducted Sensitivity Analysis
- Evaluated for Bag of Words
  - Silhouette score [Rousseeuw, 1987]
  - Subjective similarity of vectors sharing same cluster
- 8 clusters for exact Bag of Words projection
- 6 clusters for binary Bag of Words projection

COMPUTATION OF UTILITY - LOCAL OUTLIER FACTOR

- Sensitivity Analysis: range of number of neighbors in a neighborhood values evaluated for Bag of Words
  - Silhouette score
  - Subjective similarity of vectors sharing same cluster
  - Number of tweet streams labeled as outliers
- Chose number of neighbors in a neighborhood value of 20

COMPUTATION OF UTILITY - FREQUENT ITEM SETS

- Sensitivity Analysis: conducted for a range of minimum support values, for all projections
  - number of sets of size larger than 2
  - number of sets = ~100
- Minimum support of 1% for Bag of Words
  - 113 item sets

COMPUTATION OF UTILITY – FREQUENT ITEM SETS

- Emotion
  - Minimum support of .01%
  - 44 frequent item sets
- Importance
  - Minimum support of .02%
  - 92 frequent item sets
- Frequency
  - Minimum support of 1%
  - 138 frequent item sets

COMPUTATION OF DISTORTION

- Distortion rates for projections
  - Fraction of non-zero features lost each handle vector, when represented by projection

Emotion 333	Top 1k Frequency	Top 1k Importance	Emotion 5	Frequency 5	Importance 5
0.9993	0.6054	0.9996	0.9995	0.9597	0.9997

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- Importance and Emotion projections exhibit high distortion

COMPUTATION OF DISTORTION

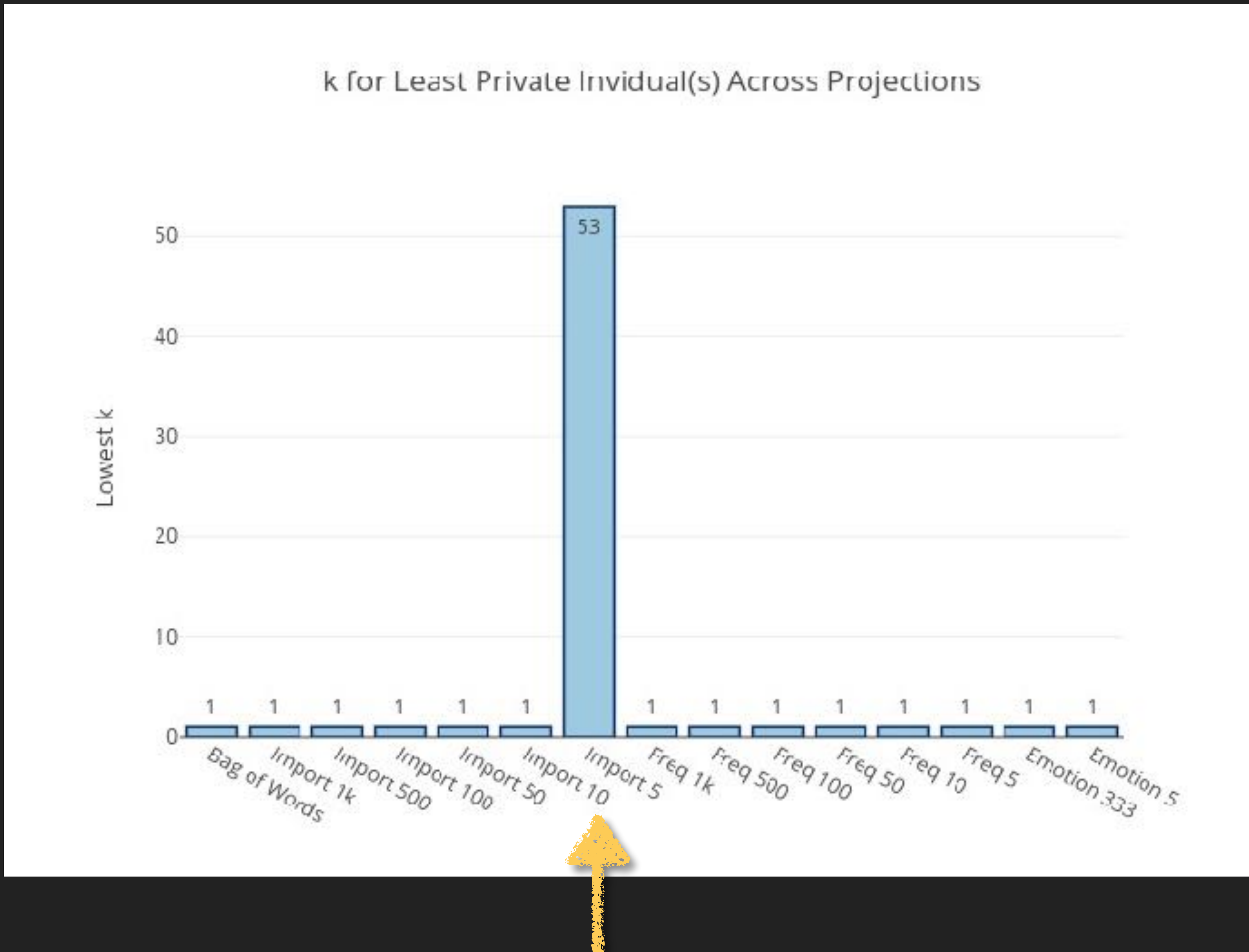
- Distortion rates for projections
  - Fraction of non-zero features lost each handle vector, when represented by projection

Emotion 333	Top 1k Frequency	Top 1k Importance	Emotion 5	Frequency 5	Importance 5
0.9993	0.6054	0.9996	0.9995	0.9597	0.9997

- Comparatively low distortion for Frequency projection

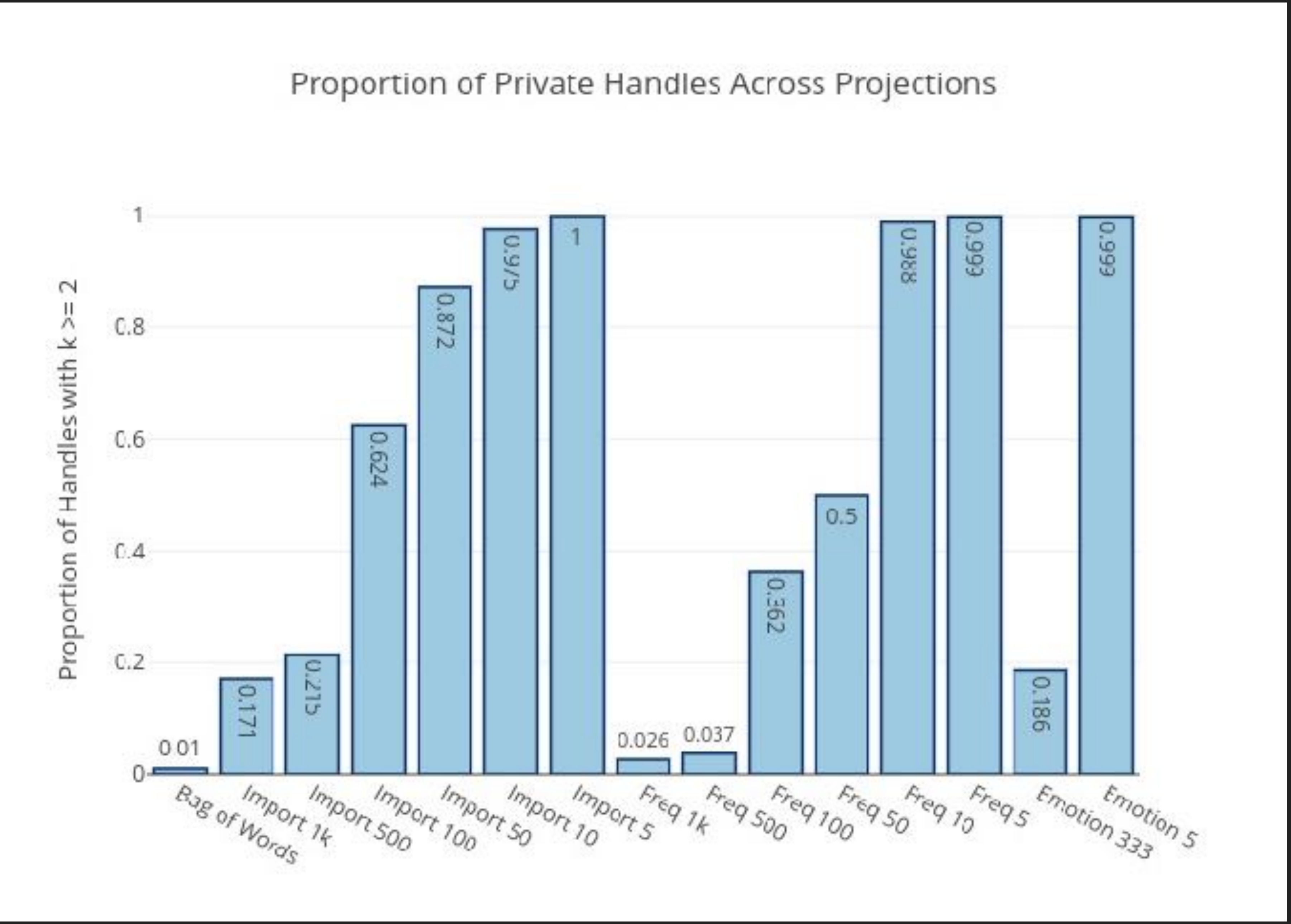
PRIVACY – K ANONYMOUS VECTOR METRIC

- Binary
- Lowest k for each projection
- Only Importance projection achieves privacy for all users



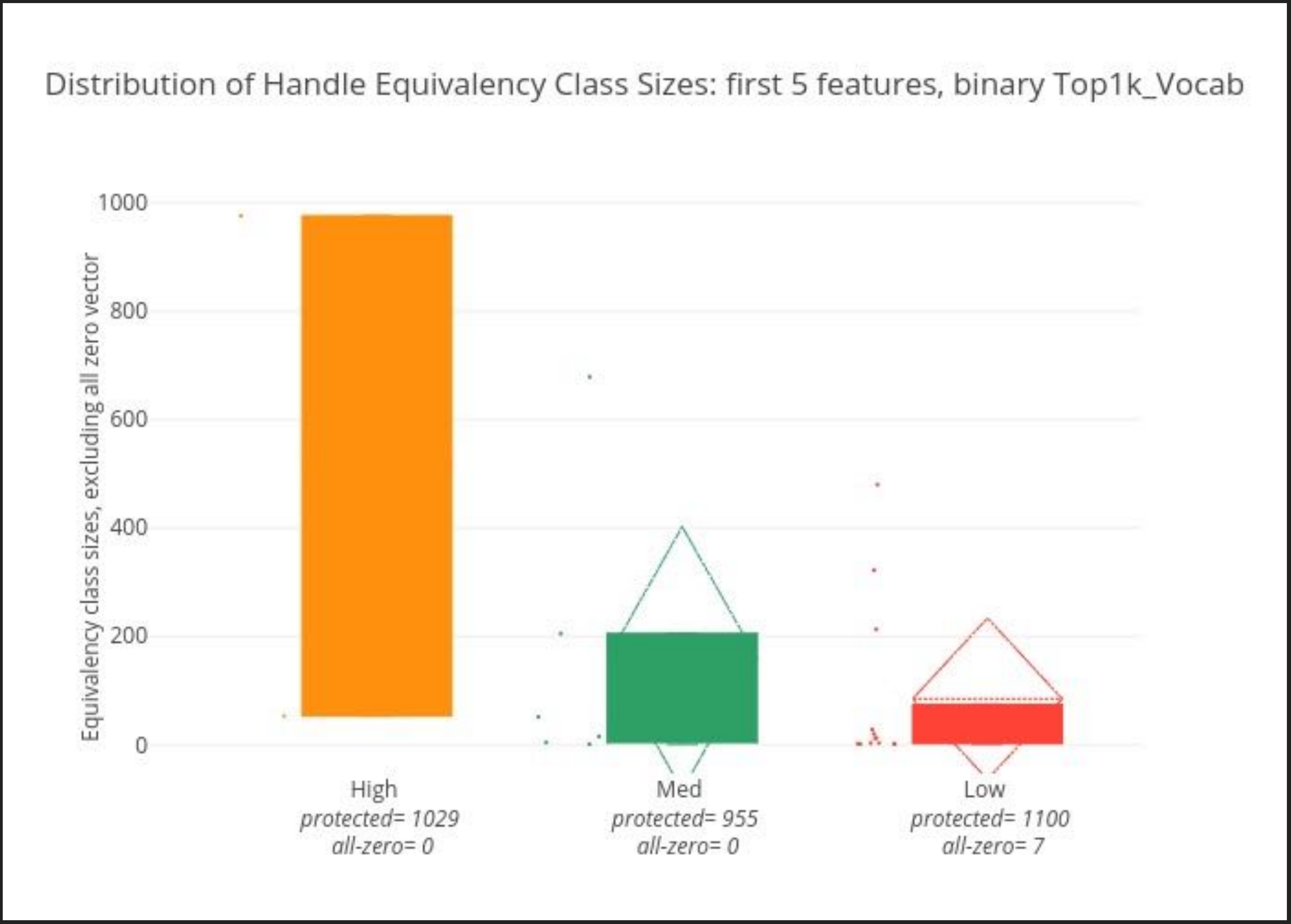
PRIVACY – K ANONYMOUS VECTOR METRIC

- Proportion of handles with privacy (k>=2) for each projection
- Low privacy unless small feature spaces used



PRIVACY – ACROSS ENGAGEMENT LEVELS – FREQUENCY PROJECTION

- High average *k* for Frequency projection, small vector size
- More engagement corresponds to higher average *k*
- All individuals protected



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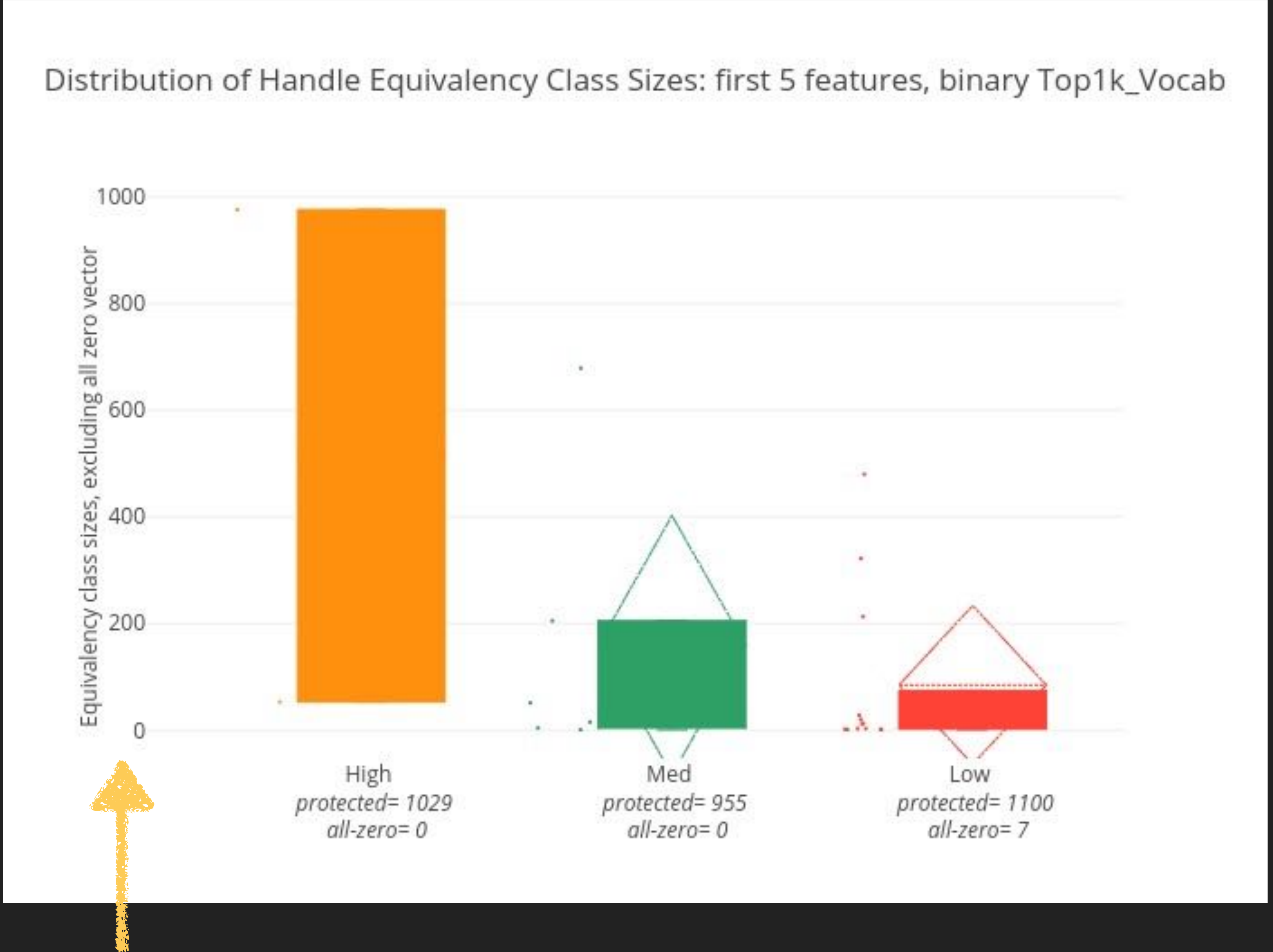

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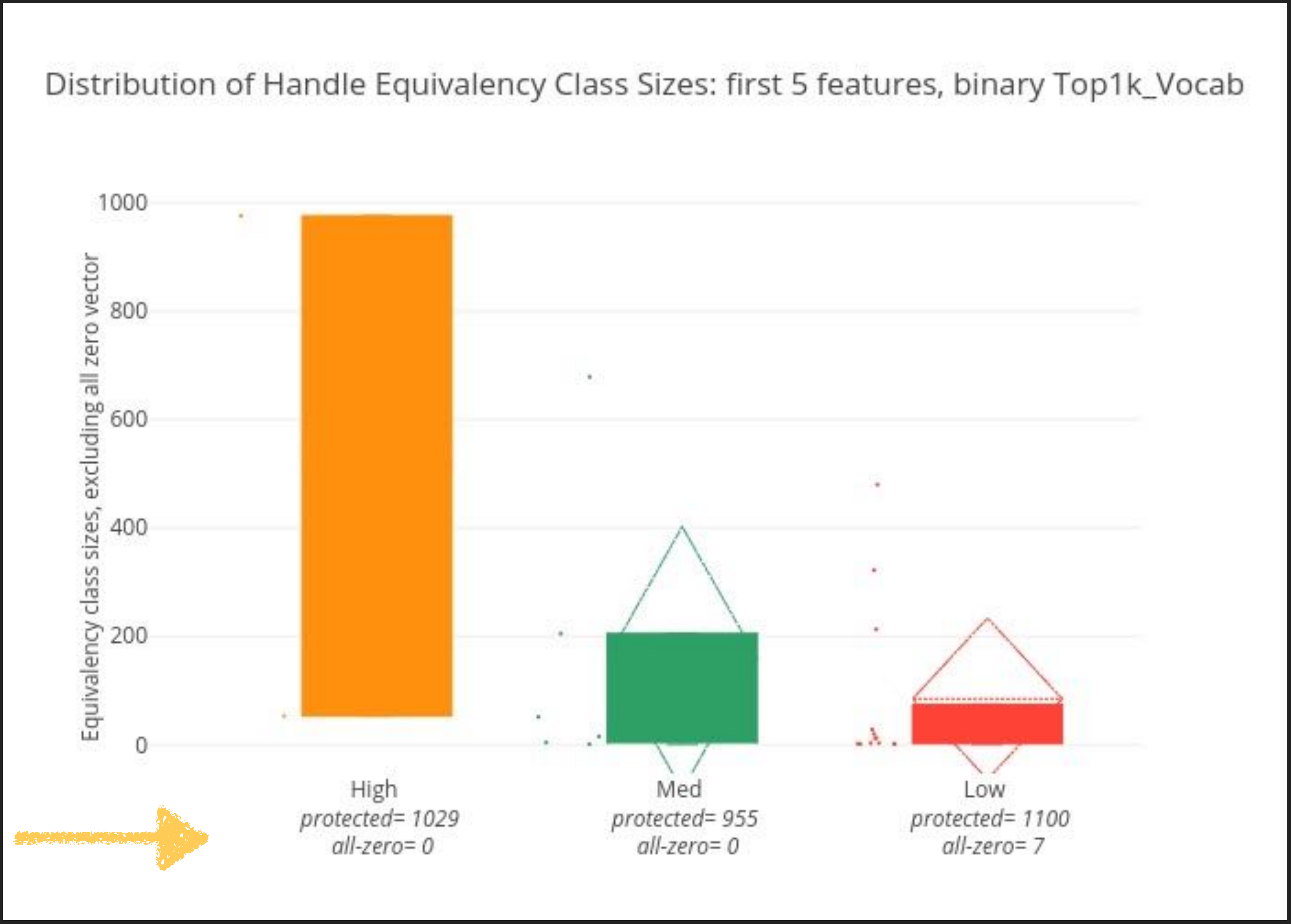

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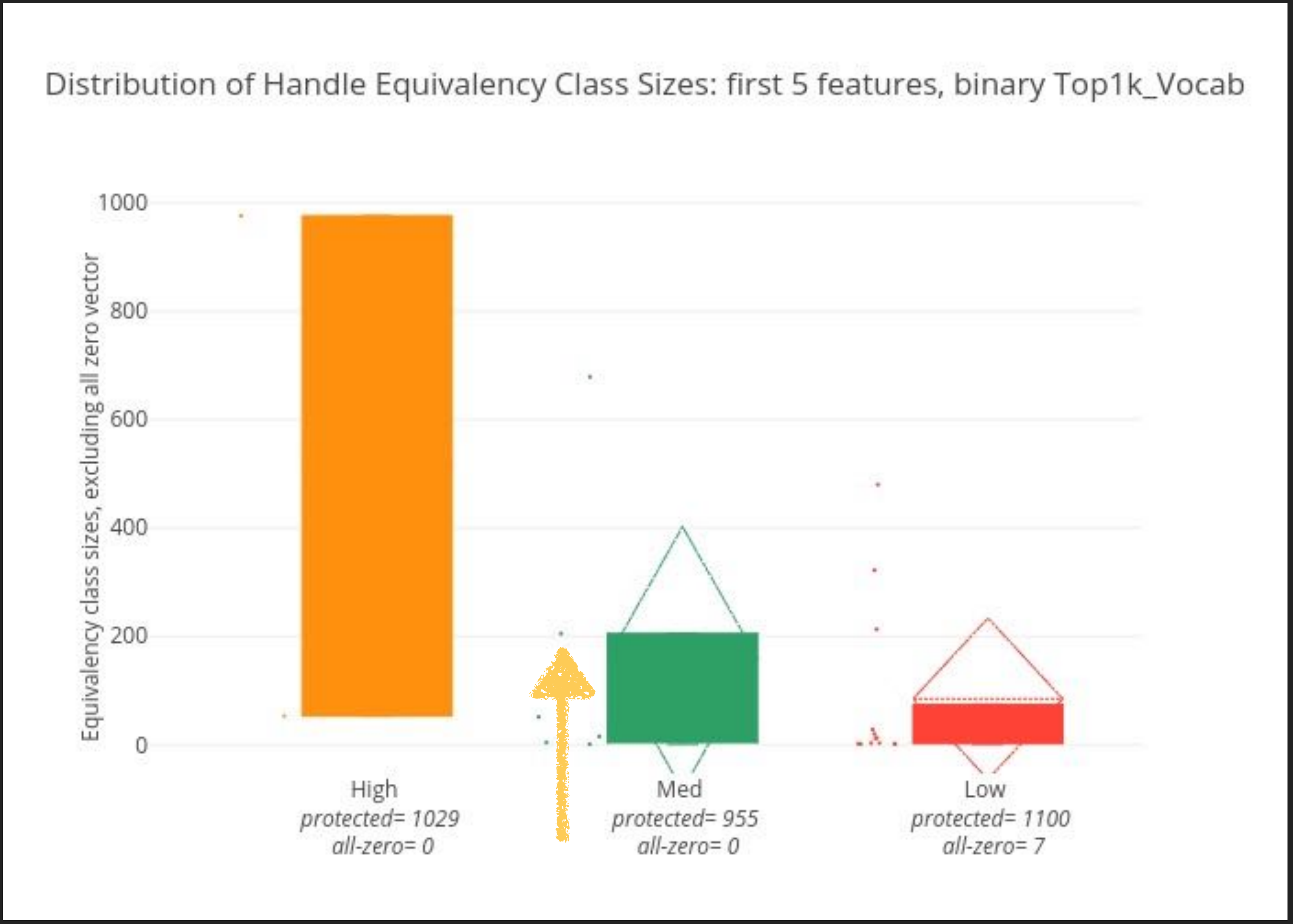

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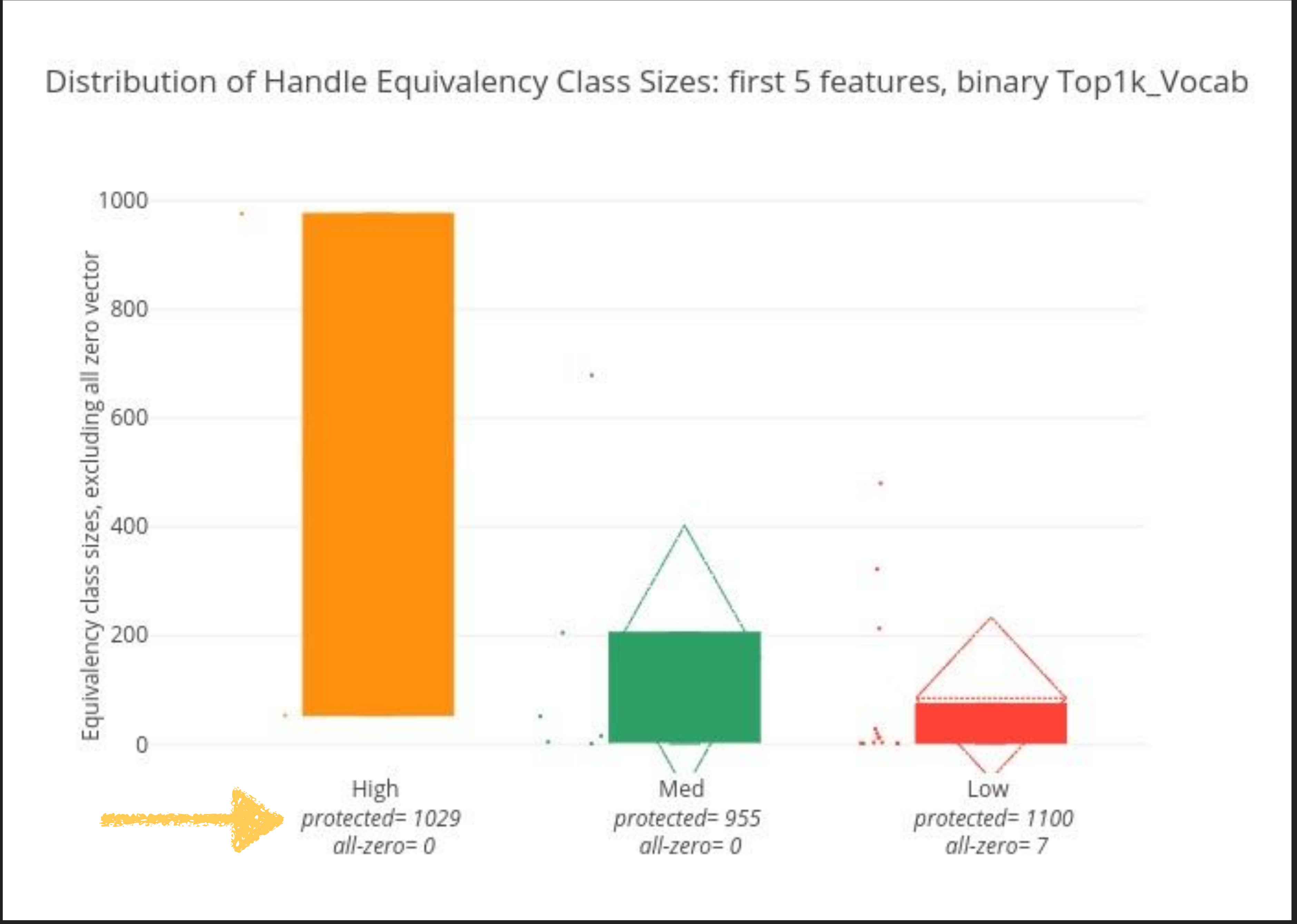

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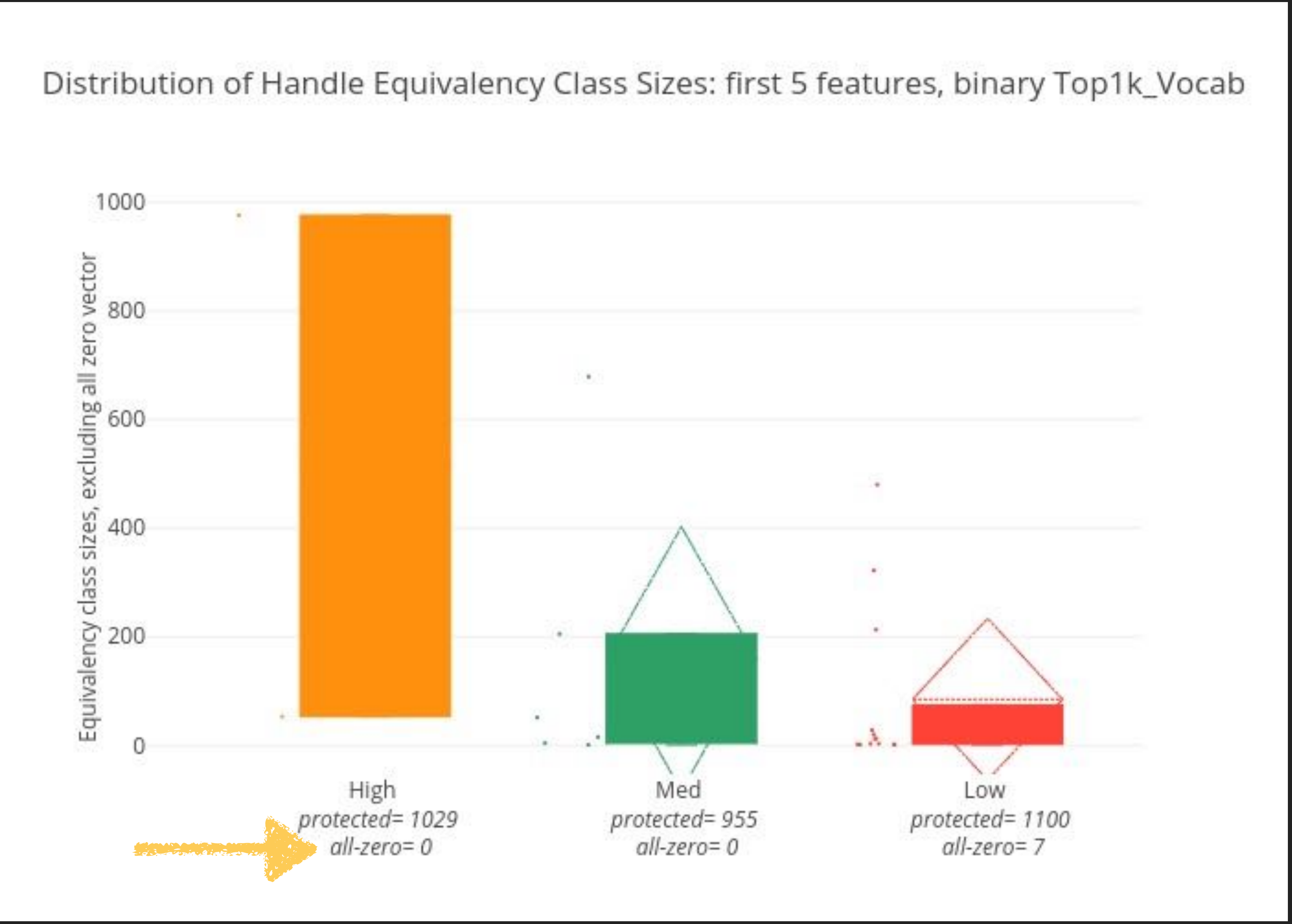
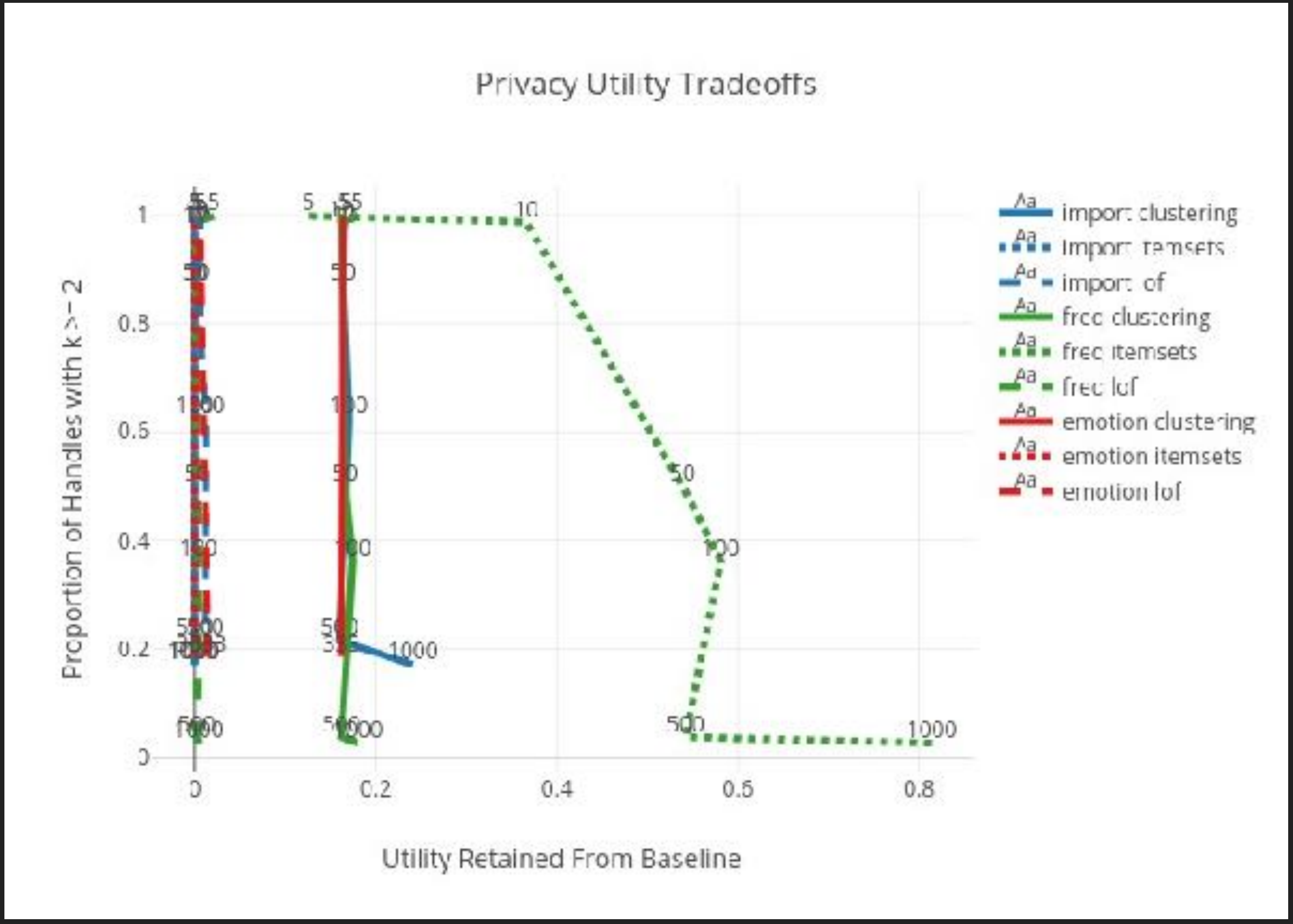


RESULTS - PRIVACY UTILITY TRADEOFFS

- Utility retention and proportion of individuals with privacy for a range of projection feature space sizes
- Only meaningful utility retention for clustering task and frequent item set mining task



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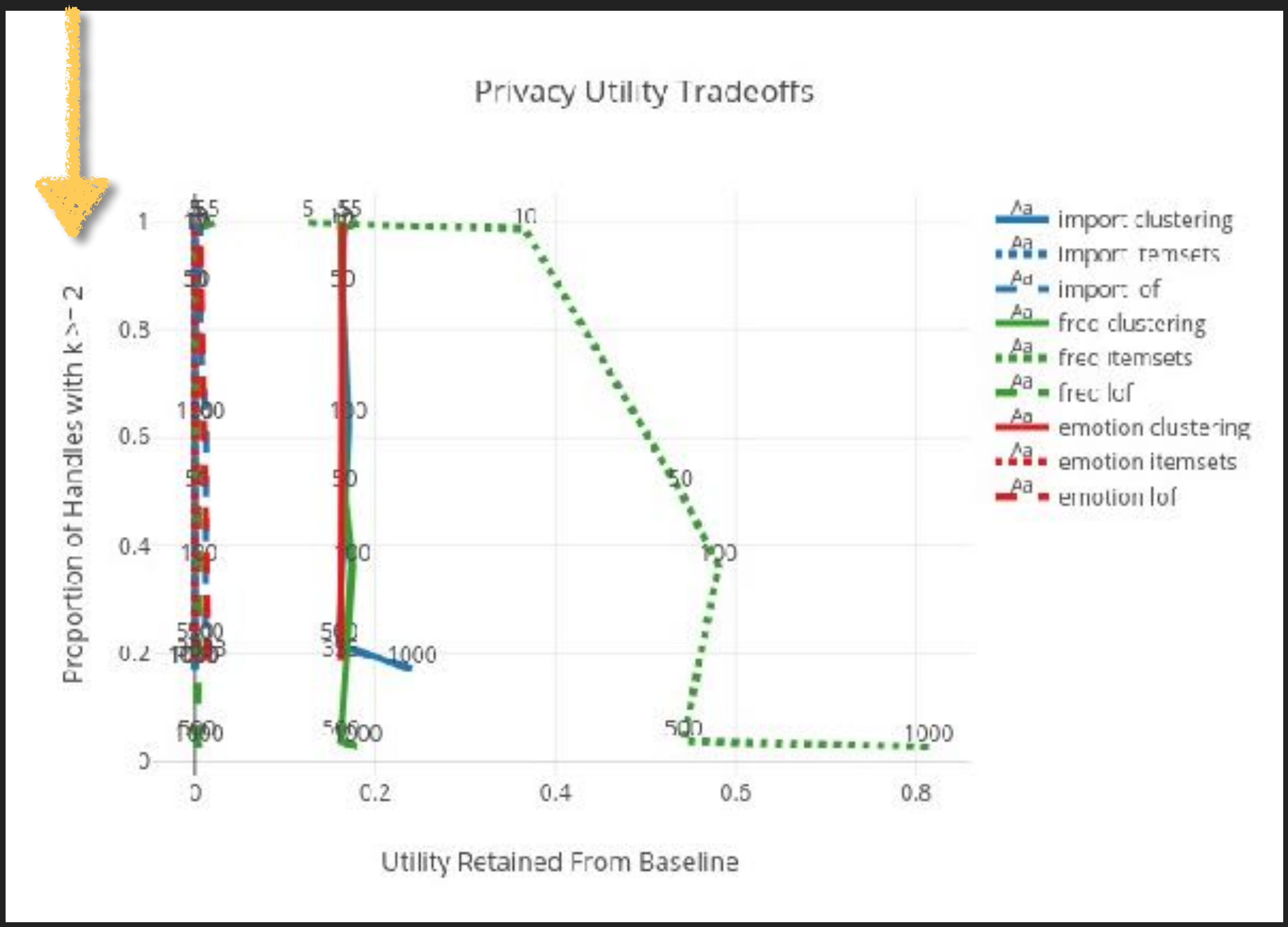

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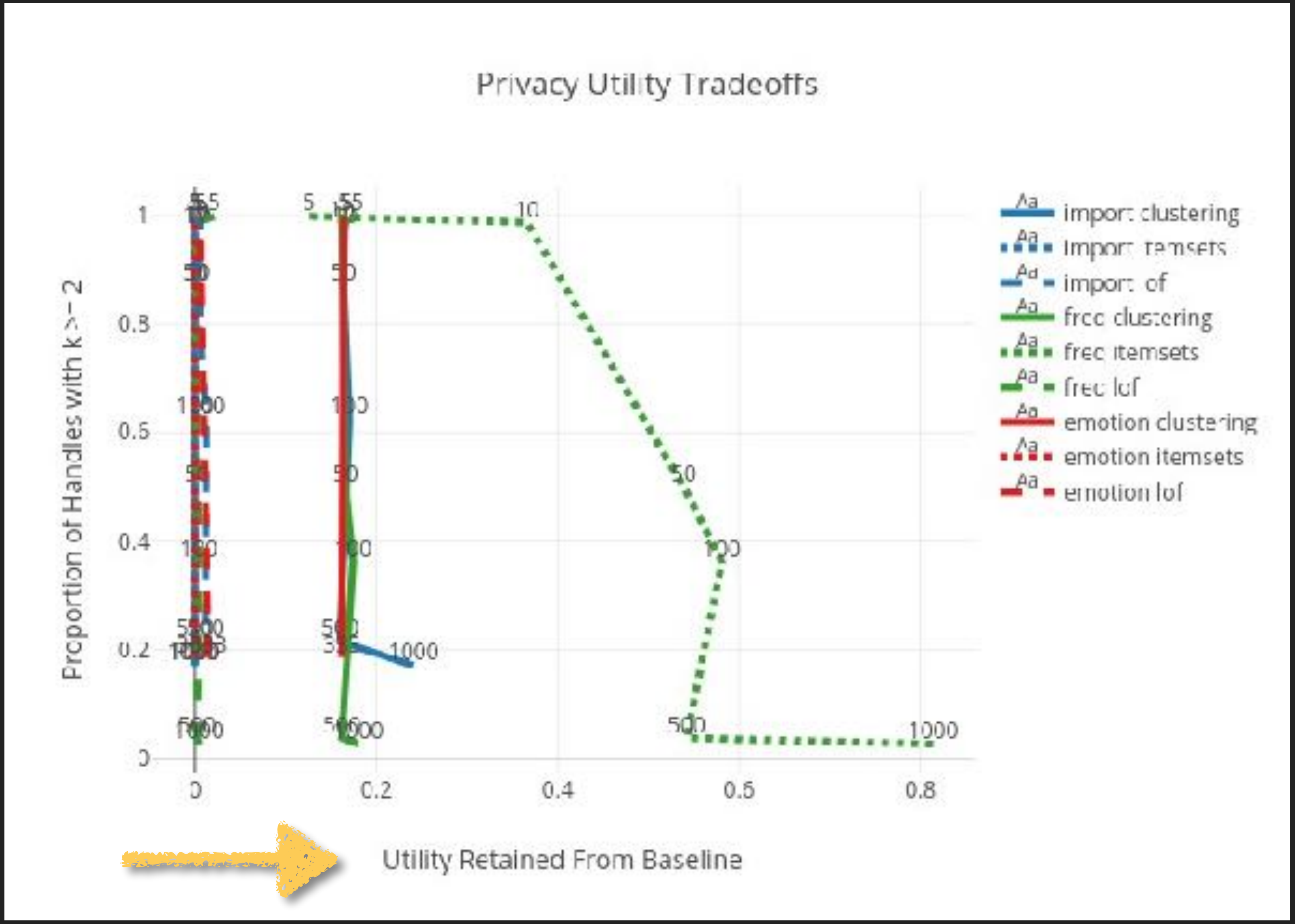

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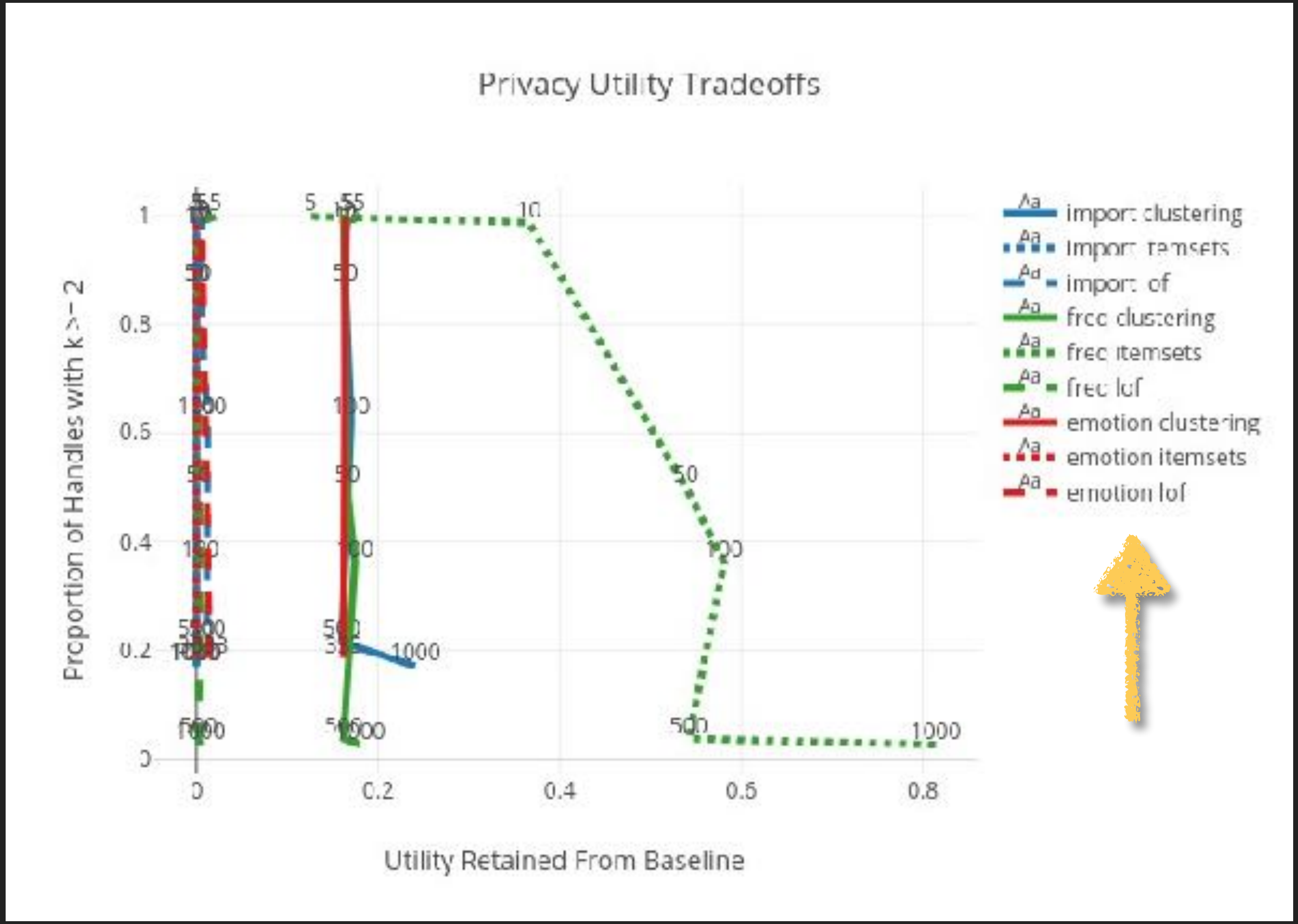

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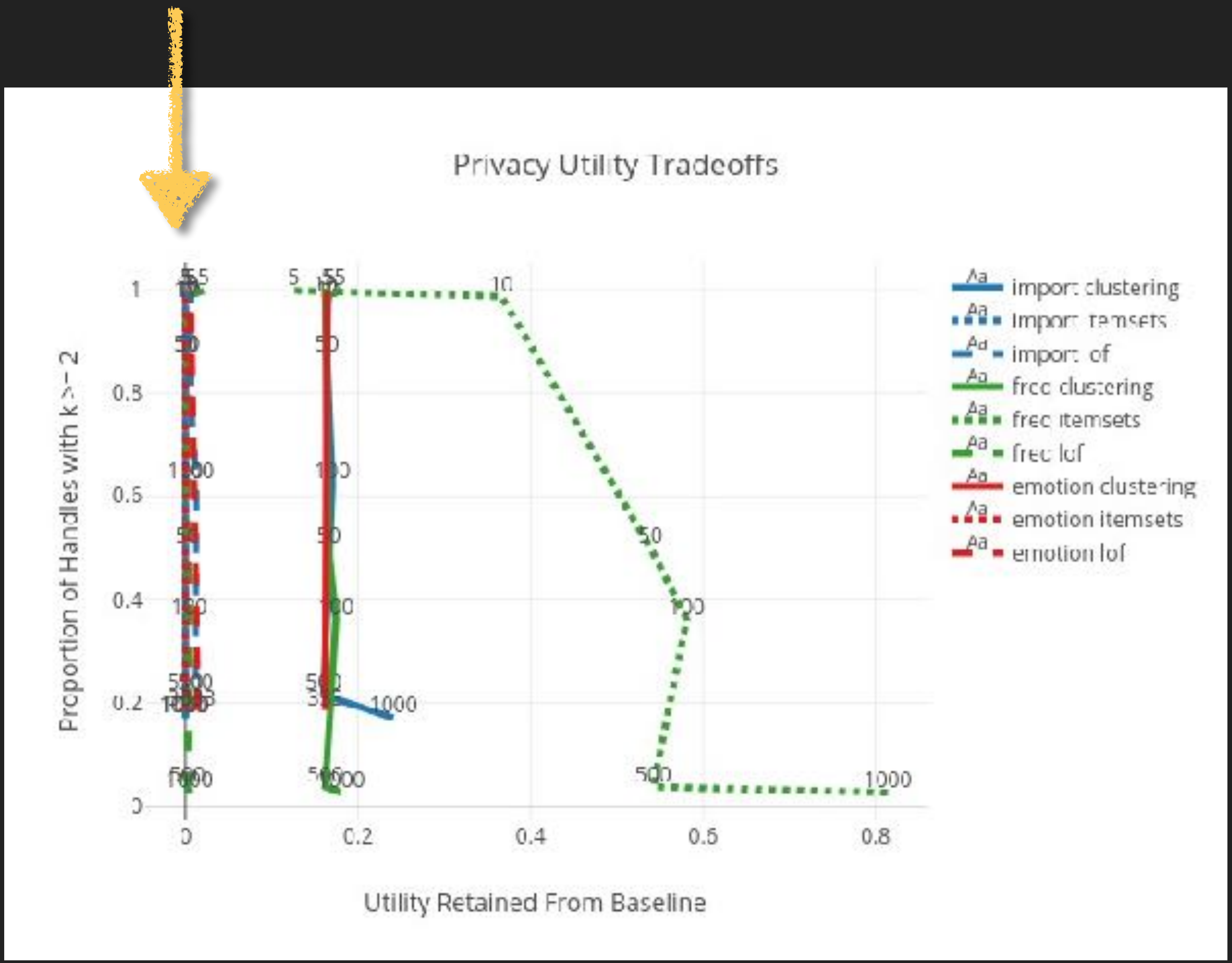

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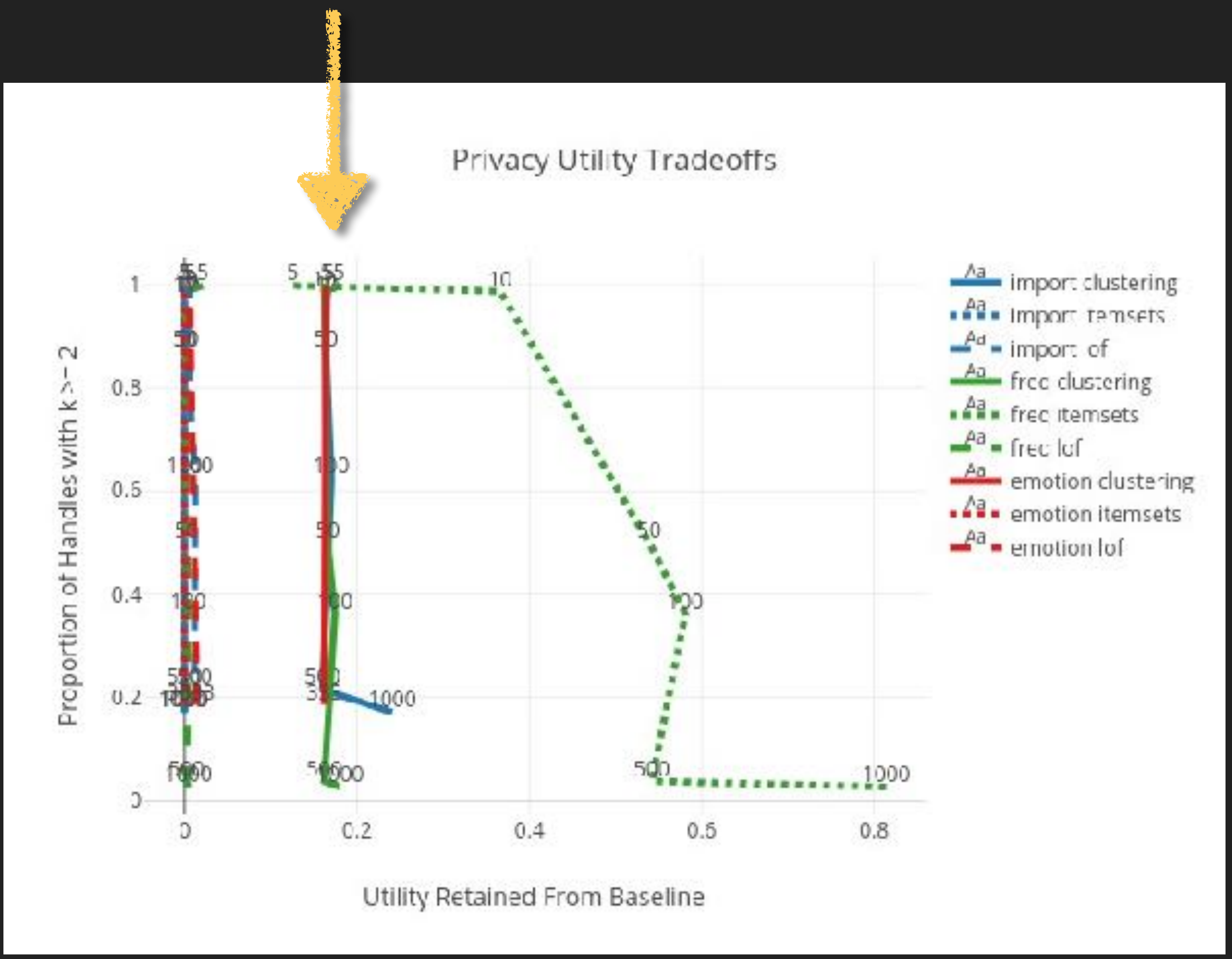

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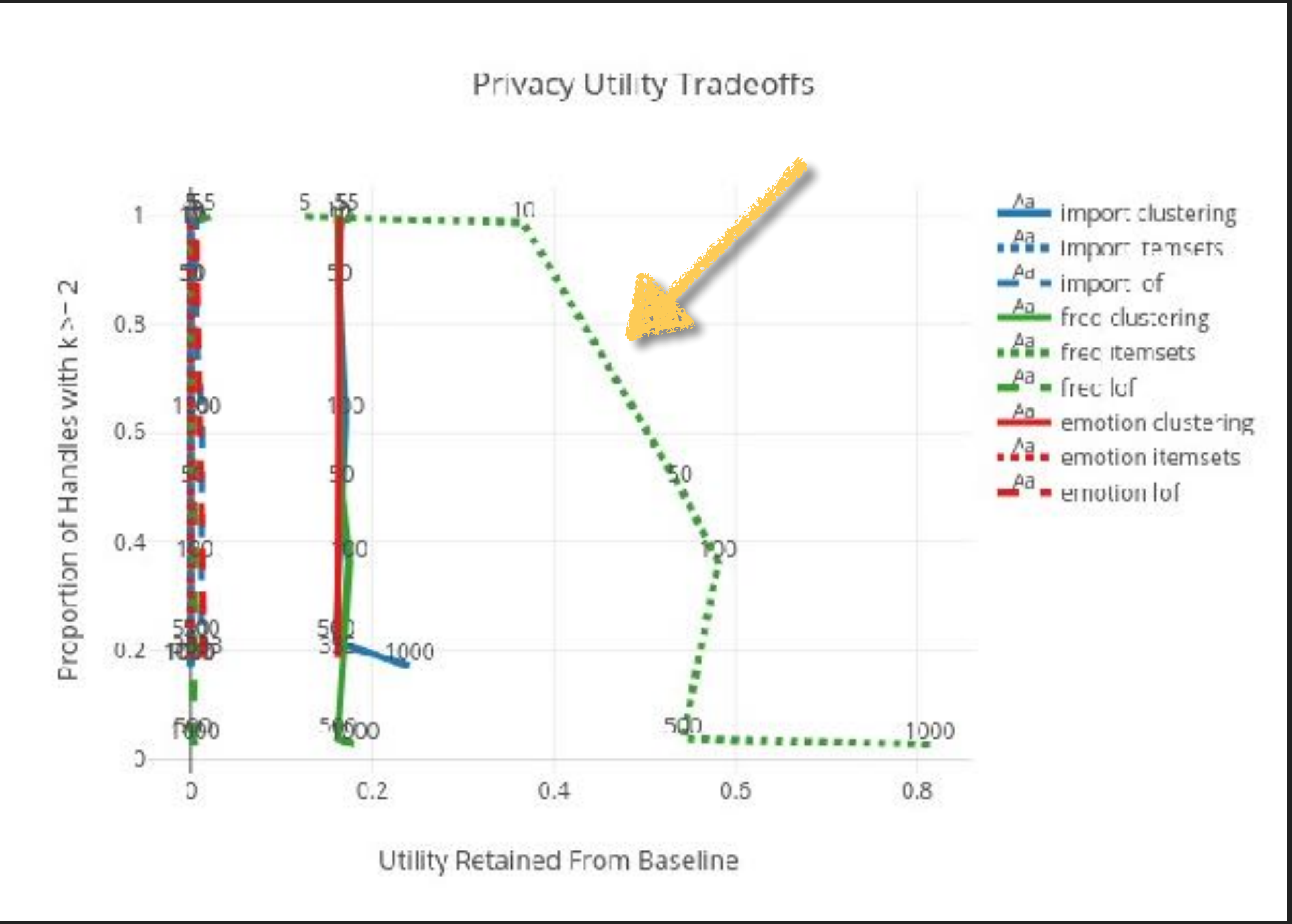

RESULTS - SUMMARY

- Difficult to obtain k anonymous vector privacy measure greater than 1 for all tweet streams without a high loss of data utility
- Vector length had little or no impact on utility for all projections, besides item set mining on Frequency projection
- For Frequency projection, interesting how frequent item set mining performance changes according to vector length
- The relationship between utility and privacy is very task dependent
  - Shouldn't expect general solution - projection selection should be task dependent

CONTRIBUTIONS

- Novel analysis of social media distinguishability
- Framework for analyzing privacy-utility tradeoffs of different representations of social media texts posts
- Empirical analysis showing users are only private if represented by a small number of features, but this results in high data utility loss

FUTURE WORK

- Better understand what types of transformations (including mathematical transformations) help maintain any level of utility for specific data mining tasks
  - Because of sparseness of our projections, mathematical transformation have potential for increased privacy with low impact on data utility.
- Impact of retweet frequency on privacy

REFERENCES

- Dodds, et al. Human language reveals a universal positivity bias. *Proceedings of the National Academy of Sciences*, 112(8):2389–2394, 2015.
- Horspool and Cormack. Constructing word-based text compression algorithms. In *Data Compression Conference*, 1992., pages 62–71, March 1992.
- Li and Li. On the tradeoff between privacy and utility in data publishing. In *Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '09, pages 517–526, New York, NY, USA, 2009. ACM.
- Qadir and Riloff. Bootstrapped learning of emotion hashtags #hashtags4you. 2013.

REFERENCES

- Roberts et al. Empatweet: Annotating and detecting emotions on twitter. 2012.
- L. Singh et al. Public information exposure detection: Helping users understand their web foot- prints. In *2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, pages 153–161, Aug 2015.
- Ian Witten et al. Semantic and generative models for lossy text compression. 37, 07 2000.
- Yang et al. Building emotion lexicon from weblog corpora. In *Proceedings of the 45th Annual Meeting of the ACL on Interactive Poster and Demonstration Sessions, ACL '07*, pages 133–136, Stroudsburg, PA, USA, 2007. Association for Computational Linguistics.
- Sweeney. *k*-anonymity: a model for protecting privacy. 2002.

QUESTIONS

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