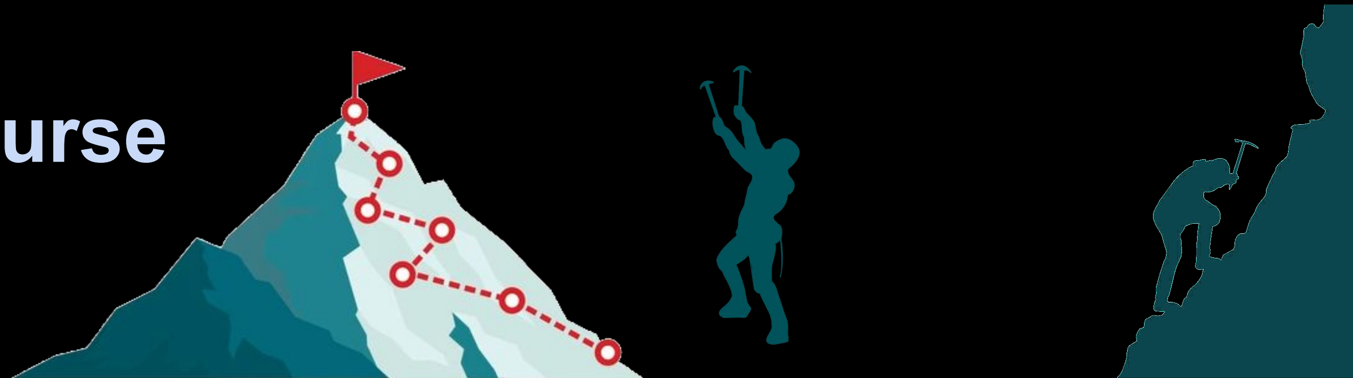
Human-Centered NLP

CSE 538

NLP, The Course



Overall NLP Concept

I. Syntax

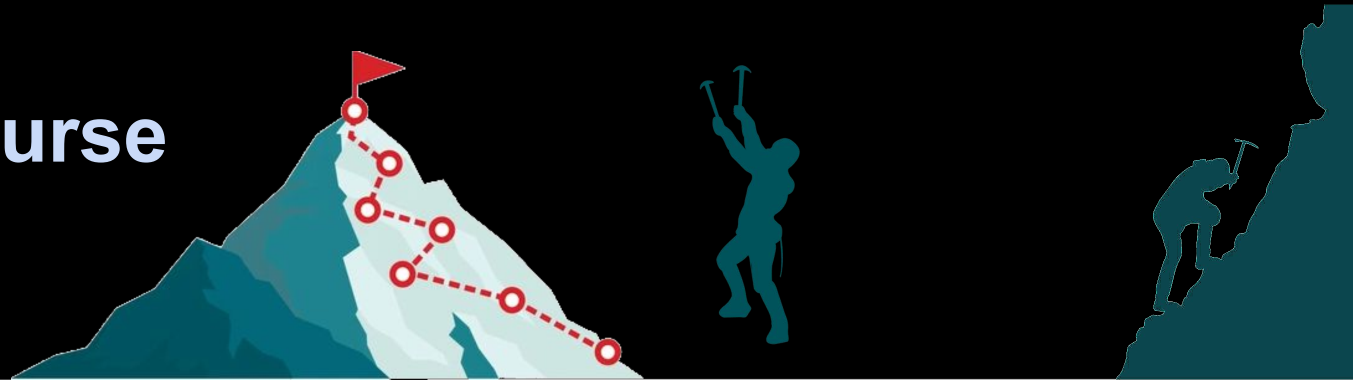
II. Semantics

Overall NLP Concept

III. Language Modeling

IV. Applications

NLP, The Course



Overall NLP Concept

I. Syntax

Introduction to NLP; Tokenization; Words Corpora

One-hot, and Multi-hot encoding.
Parts-of-Speech; Named Entities;

Parsing; Verbal Predicates;Dependency Parsing

II. Semantics

Dependency Parsing; Word Sense Disambiguation

Vector Semantics (Embeddings), Word2vec

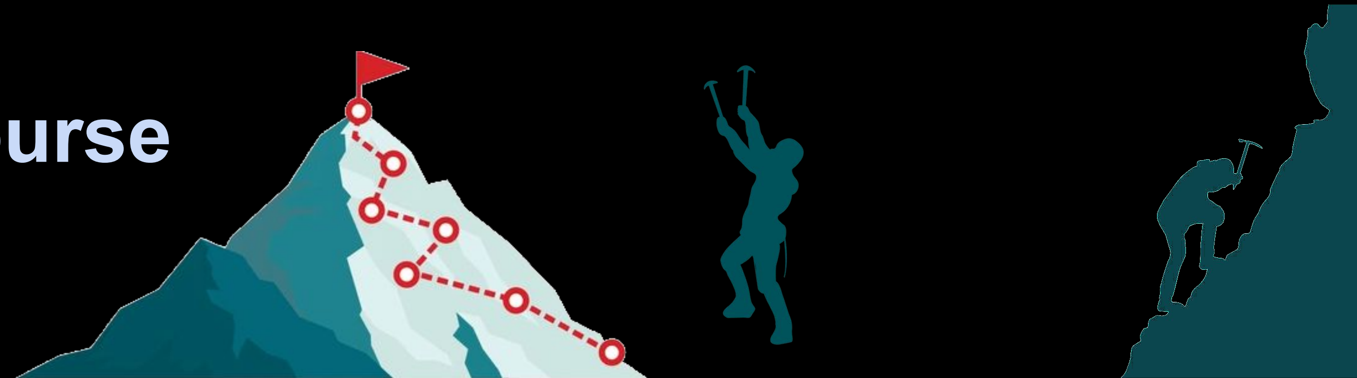
Probabilistic Language Models
Ngram Classifier, Topic Modeling

Overall NLP Concept

III. Language Modeling

IV. Applications

NLP, The Course



Overall NLP Concept

I. Syntax

Introduction to NLP; Tokenization; Words Corpora

One-hot, and Multi-hot encoding.
Parts-of-Speech; Named Entities;

Parsing; Verbal Predicates;Dependency Parsing

II. Semantics

Dependency Parsing; Word Sense Disambiguation

Vector Semantics (Embeddings), Word2vec

Probabilistic Language Models
Ngram Classifier, Topic Modeling

Overall NLP Concept

III. Language Modeling

Ethical Considerations

Masked Language Modeling (autoencoding)

Generative Language Modeling (autoregressive)

Applying LMs

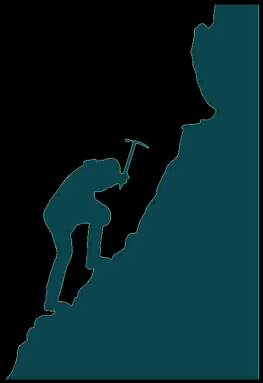
IV. Applications

Language and Psychology
(advanced sentiment)

Speech and Audio Processing, Dialog (chatbots)

Question Answering, Translation

NLP The Course



Overall NLP Concept

I. Syntax

Introduction to NLP; Tokenization; Words Corpora

One-hot, and Multi-hot encoding. Parts-of-Speech; Named Entities;

Parsing; Verbal Predicates;Dependency Parsing

II. Semantics

Dependency Parsing; Word Sense Disambiguation

Vector Semantics (Embeddings), Word2vec

Probabilistic Language Models Ngram Classifier, Topic Modeling

Overall NLP Concept

III. Language Modeling

Ethical Considerations

Masked Language Modeling (autoencoding)

Generative Language Modeling (autoregressive)

Applying LMs

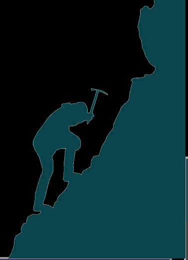
IV. Applications

Language and Psychology (advanced sentiment)

Speech and Audio Processing, Dialog (chatbots)

Question Answering, Translation

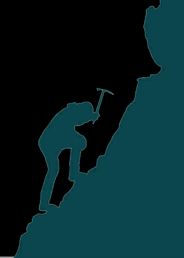
NLP The Course



Overall NLP Concept	Computation or ML
I. Syntax | Classification	
Introduction to NLP; Tokenization; Words Corpora	
One-hot, and Multi-hot encoding. Parts-of-Speech; Named Entities;	
Parsing; Verbal Predicates;Dependency Parsing	
II. Semantics | Probabilistic Models	
Dependency Parsing; Word Sense Disambiguation	
Vector Semantics (Embeddings), Word2vec	
Probabilistic Language Models Ngram Classifier, Topic Modeling	

Overall NLP Concept	Computation or ML
III. Language Modeling | Transformers	
Ethical Considerations	
Masked Language Modeling (autoencoding)	
Generative Language Modeling (autoregressive)	
Applying LMs	
IV. Applications | Custom Statistical or Symbolic	
Language and Psychology (advanced sentiment)	
Speech and Audio Processing, Dialog (chatbots)	
Question Answering, Translation	

NLP The Course



Overall NLP Concept	Computation or ML
I. Syntax | Classification	
Introduction to NLP; Tokenization; Words Corpora	Regular Expressions; Edit Distance
One-hot, and Multi-hot encoding. Parts-of-Speech; Named Entities;	Maximum Entropy Classifier (LogReg), Gradient Descent,
Parsing; Verbal Predicates;Dependency Parsing	Cross Validation; Regularization Accuracy Metrics; Shift Reduce
II. Semantics | Probabilistic Models	
Dependency Parsing; Word Sense Disambiguation	Term Probabilities; N-d Vectors
Vector Semantics (Embeddings), Word2vec	LDA, Skipgram Model
Probabilistic Language Models Ngram Classifier, Topic Modeling	markov assumption, chain rule, smoothing

Overall NLP Concept	Computation or ML
III. Language Modeling | Transformers	
Ethical Considerations	Model cards, Pred Bias Frmwrk
Masked Language Modeling (autoencoding)	Neural Networks; Backprop Cross-Entropy Loss Self-Attention,
Generative Language Modeling (autoregressive)	Positional encodings The Transformer: Beam Search
Applying LMs	Fine-Tuning, zero-/few-shot, Instruction tuning
IV. Applications | Custom Statistical or Symbolic	
Language and Psychology (advanced sentiment)	Differential Language Analysis; Adaptive Modeling; Human LMing
Speech and Audio Processing, Dialog (chatbots)	Wave Transforms; RNNs
Question Answering, Translation	Multihop Reasoning

NLP The Course

Overall NLP Concept	Computation or ML
I. Syntax | Classification	
Introduction to NLP; Tokenization; Words Corpora	Regular Expressions; Edit Distance
One-hot, and Multi-hot encoding. Parts-of-Speech; Named Entities;	Maximum Entropy Classifier (LogReg), Gradient Descent,
Parsing; Verbal Predicates;Dependency Parsing	Cross Validation; Regularization Accuracy Metrics; Shift Reduce
II. Semantics | Probabilistic Models	
Dependency Parsing; Word Sense Disambiguation	Term Probabilities; N-d Vectors
Vector Semantics (Embeddings), Word2vec	LDA, Skipgram Model
Probabilistic Language Models Ngram Classifier, Topic Modeling	markov assumption, chain rule, smoothing

Overall NLP Concept	Computation or ML
III. Language Modeling | Transformers	
Ethical Considerations	Model cards, Pred Bias Frmwrk
Masked Language Modeling (autoencoding)	Neural Networks; Backprop Cross-Entropy Loss Self-Attention,
Generative Language Modeling (autoregressive)	Positional encodings The Transformer: Beam Search
Applying LMs	Fine-Tuning, zero-/few-shot, Instruction tuning
IV. Applications | Custom Statistical or Symbolic	
Language and Psychology (advanced sentiment)	**Differential Language Analysis; Adaptive Modeling; Human LMing**
Speech and Audio Processing, Dialog (chatbots)	Wave Transforms; RNNs
Question Answering, Translation	Multihop Reasoning

Natural Language Processing

Psychological & Health Sciences

Extraversion

Schwartz, H. A., Eichstaedt, ... & Ungar. (2013). Personality, gender, and age in the language of social media: The open-vocabulary approach. *PloS one, 8(9)*.

Introversion

Schwartz, H. A., Eichstaedt, ... & Ungar. (2013). Personality, gender, and age in the language of social media: The open-vocabulary approach. *PloS one, 8(9)*.

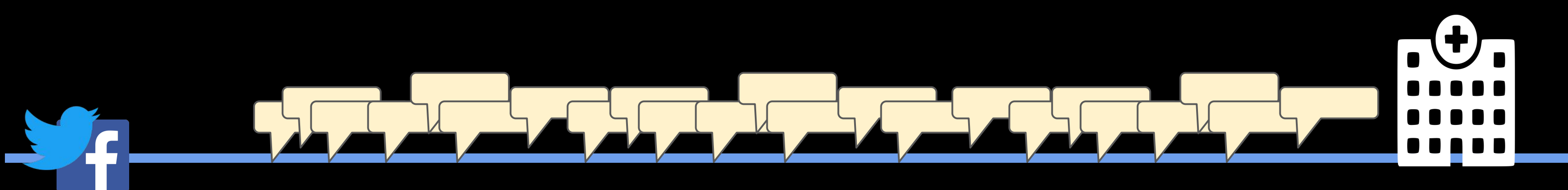
Natural Language Processing

Psychological & Health Sciences

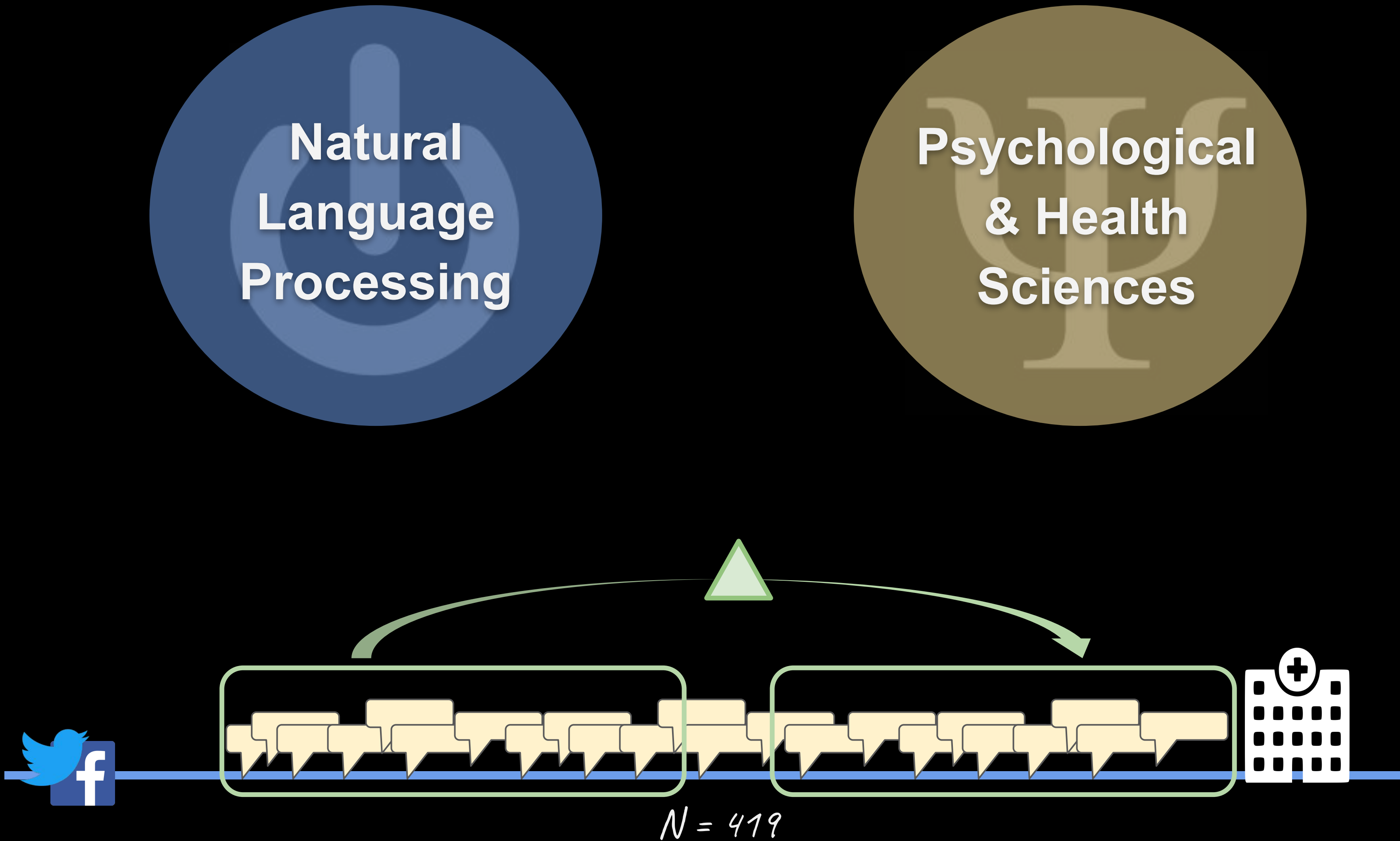
Schwartz, H. A., Eichstaedt, ... & Ungar. (2013). Personality, gender, and age in the language of social media: The open-vocabulary approach. *PloS one, 8(9)*.

Natural Language Processing

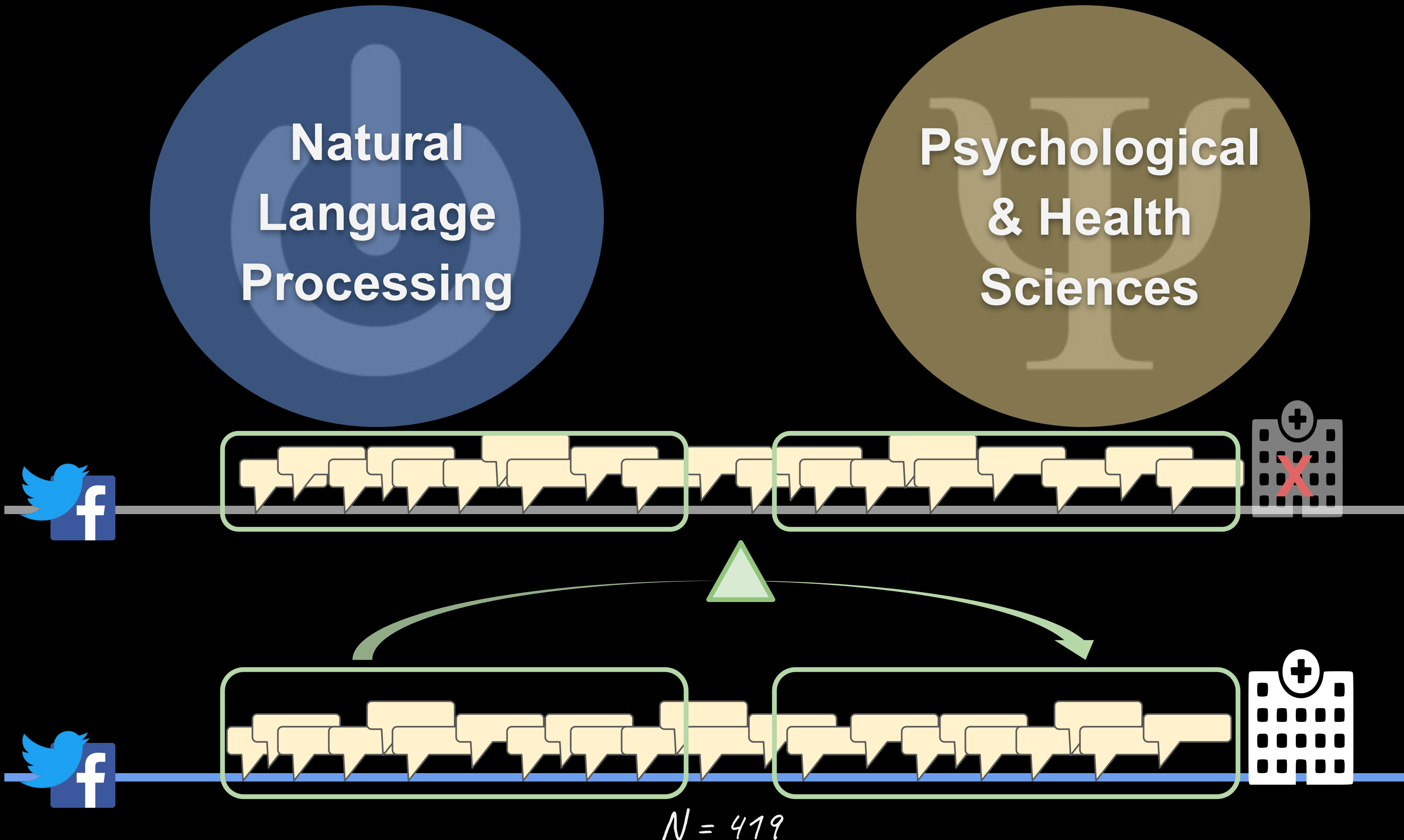
Psychological & Health Sciences



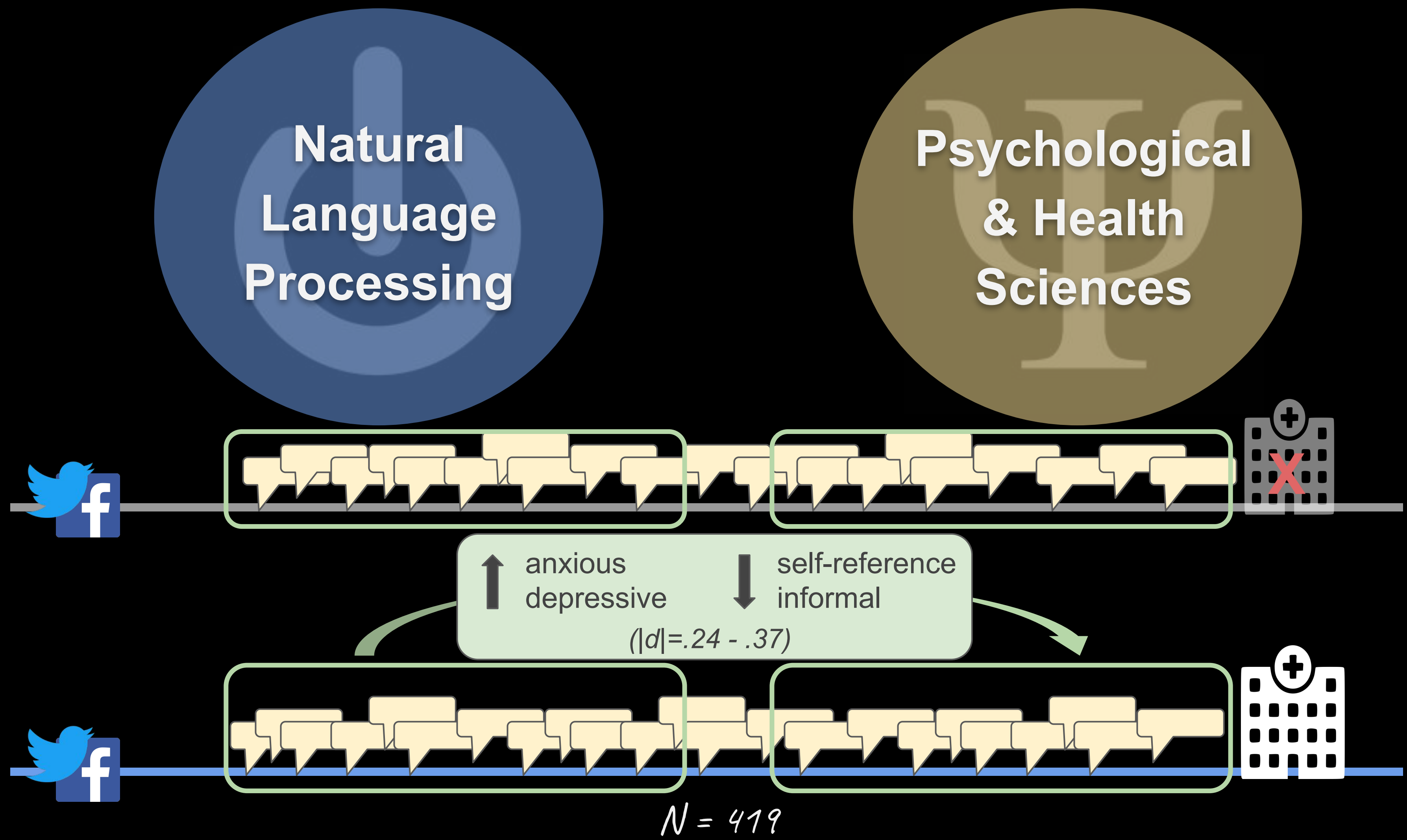
Guntuku, S. C., Schwartz, H. A., Kashyap, A., Gaulton, J. S., Stokes, D. C., Asch, D. A., ... & Merchant, R. M. (2020). Variability in Language used on Social Media prior to Hospital Visits. *Nature - Scientific Reports*, *10(1),* 1-9.



Guntuku, S. C., Schwartz, H. A., Kashyap, A., Gaulton, J. S., Stokes, D. C., Asch, D. A., ... & Merchant, R. M. (2020). Variability in Language used on Social Media prior to Hospital Visits. *Nature - Scientific Reports*, *10(1),* 1-9.



Guntuku, S. C., Schwartz, H. A., Kashyap, A., Gaulton, J. S., Stokes, D. C., Asch, D. A., ... & Merchant, R. M. (2020). Variability in Language used on Social Media prior to Hospital Visits. *Nature - Scientific Reports*, *10(1),* 1-9.



Guntuku, S. C., Schwartz, H. A., Kashyap, A., Gaulton, J. S., Stokes, D. C., Asch, D. A., ... & Merchant, R. M. (2020). Variability in Language used on Social Media prior to Hospital Visits. *Nature - Scientific Reports*, *10(1),* 1-9.

Natural Language Processing

Psychological & Health Sciences

Overly Simplified Problem-Statement:

Natural language is written by

Overly Simplified Problem-Statement:

Natural language is written by **people.**

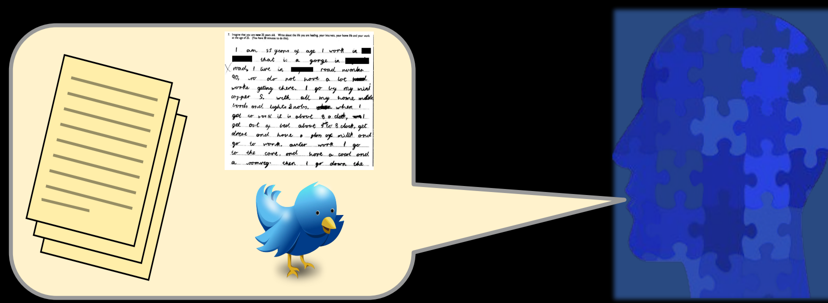
Overly Simplified Problem-Statement:

Natural language is written by **people.**

Problem

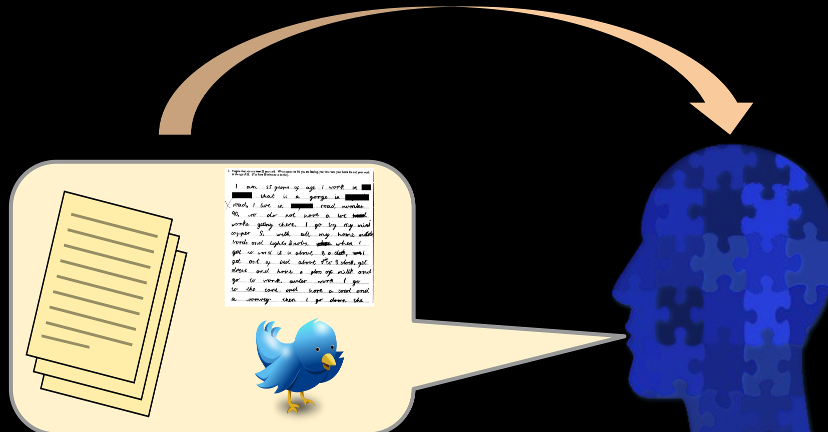
Natural language is written by **people.**

Natural language is generated by *people.*



People have different beliefs, backgrounds, styles, vocabularies, preferences, knowledge, personalities, …

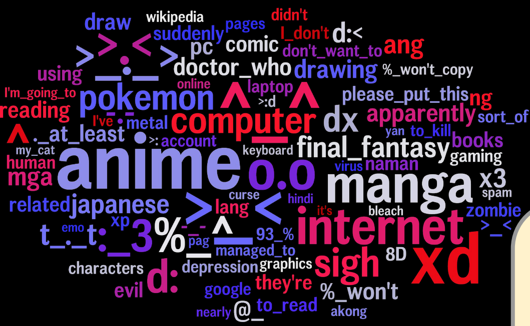
Natural language is generated by people.

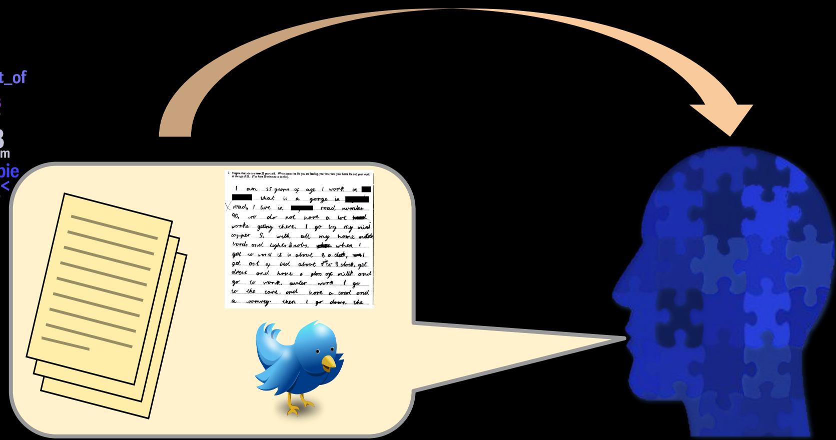


People have different beliefs, backgrounds, styles, vocabularies, preferences, knowledge, personalities, …,

and our language reflects these differences.

Natural language is generated by people.

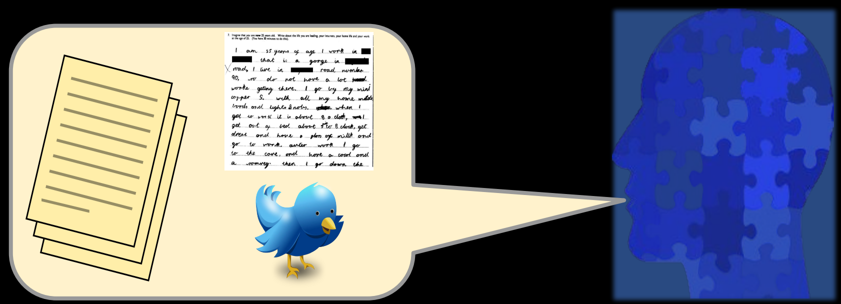




People have different beliefs, backgrounds, styles, vocabularies, preferences, knowledge, personalities, …,

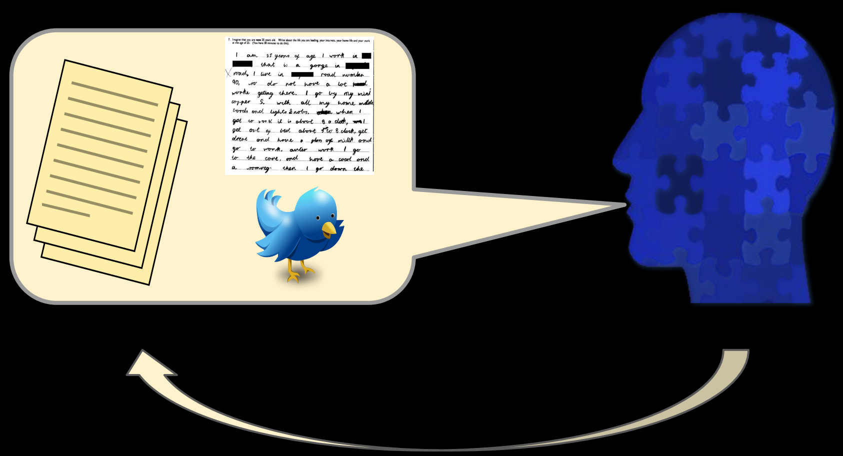
and our language reflects these differences.

Human Centered NLP:



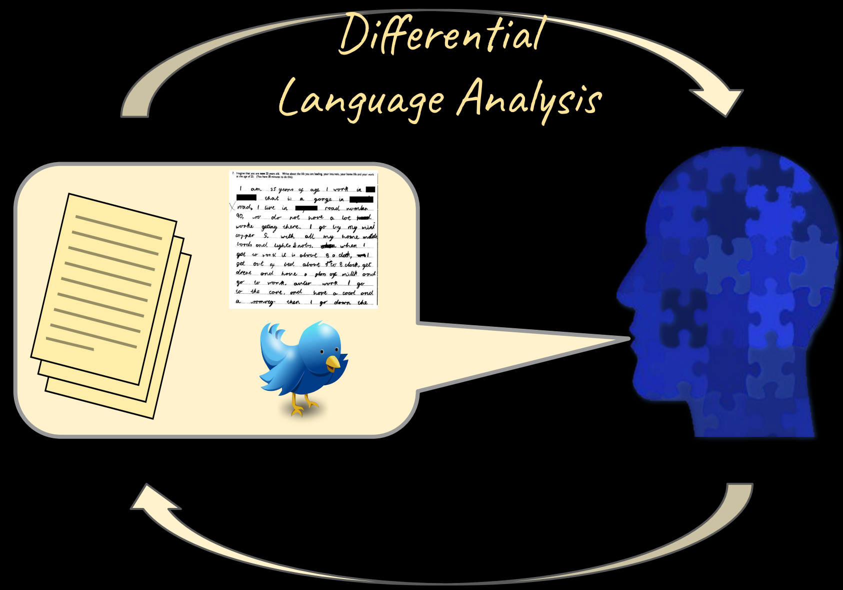
Human Centered NLP:

1. Model language as a human process



Human Centered NLP:

1. Model language as a human process
2. Use language to better understand humans.



Human-Centered NLP – We will cover:

1. Differential Language Analysis
2. Human Factor Adaptation
3. Human Language Modeling

Differential Language Analysis

Input:

Linguistic features

Human or community attribute

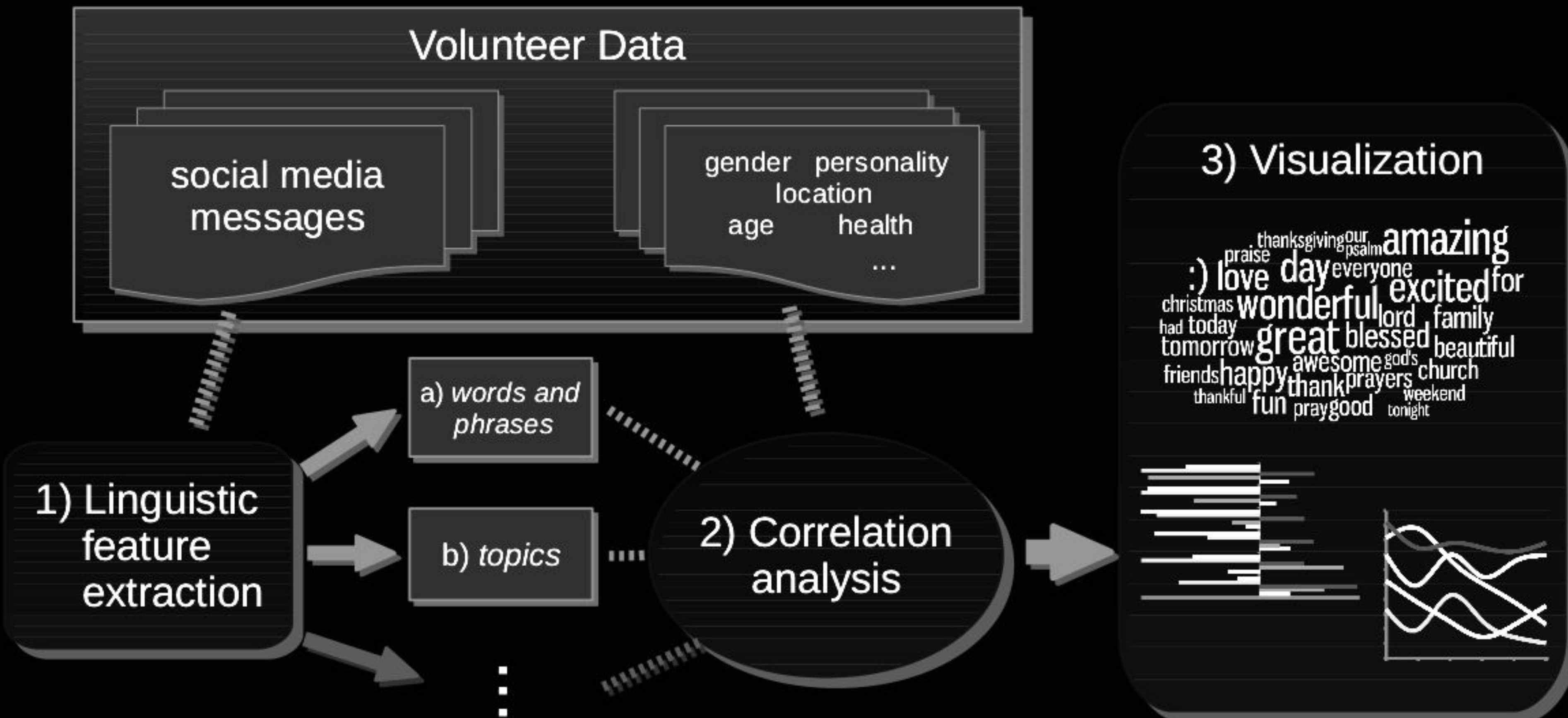
Output:

Features distinguishing attribute

Goal: Data-driven insights about an attribute

E.g. Words distinguishing communities with increases in real estate prices.

Differential Language Analysis



Differential Language Analysis

Methods of Correlation Analysis:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

- Pearson Product-Moment Correlation
  - Limitation: Doesn’t handle controls

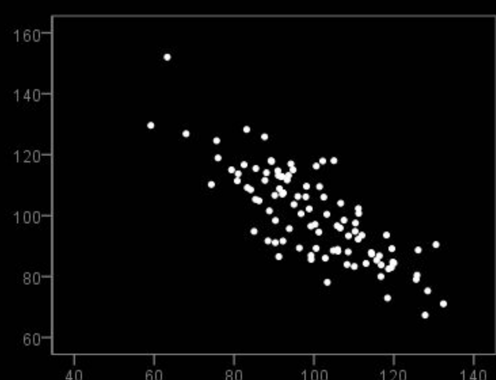
Differential Language Analysis

Methods of Correlation Analysis:

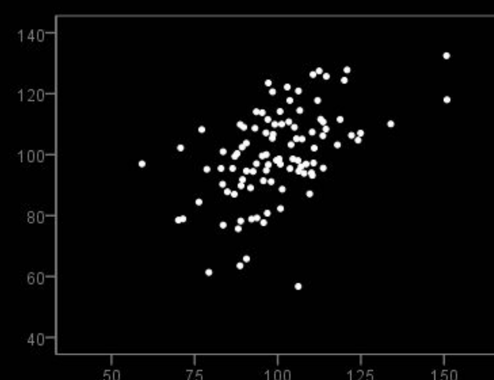
$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

- Pearson Product-Moment Correlation

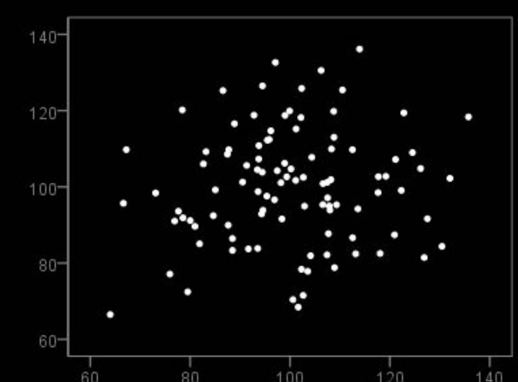
  Limitation: Doesn’t handle controls



r = -0.8



r = 0.5



r = 0.1

Differential Language Analysis

Methods of Correlation Analysis:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

- Pearson Product-Moment Correlation

    Limitation: Doesn’t handle controls

- Standardized Multivariate Linear Regression

  Fit the model: $$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_m X_{m1} + \epsilon_i$$

Differential Language Analysis

Methods of Correlation Analysis:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

- Pearson Product-Moment Correlation

  Limitation: Doesn't handle controls

- **Standardized** Multivariate Linear Regression

  Fit the model:

  $$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + ... + \beta_m X_{m1} + \epsilon_i$$

  Adjust all variables to have "mean center" and "unit variance":

Differential Language Analysis

Methods of Correlation Analysis:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

- Pearson Product-Moment Correlation
  Limitation: Doesn't handle controls

- <u>**Standardized**</u> Multivariate Linear Regression
  Fit the model:
  $$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_m X_{m1} + \epsilon_i$$

  Adjust all variables to have "mean center" and "unit variance":

$$z = \frac{x - \mu}{\sigma}$$

$\mu =$ Mean
$\sigma =$ Standard Deviation

Differential Language Analysis

Methods of Correlation Analysis:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

- Pearson Product-Moment Correlation

  Limitation: Doesn't handle controls

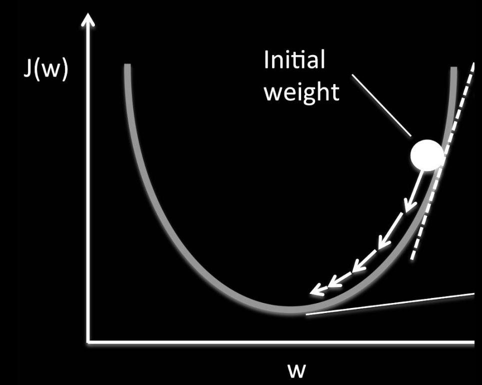
- Standardized Multivariate Linear Regression

  Fit the model:

  $$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_m X_{m1} + \epsilon_i$$

  Option 1: Gradient Descent:

  $J = \sum (y - \hat{y})^2$ -- "Sum of Squares" Error



Differential Language Analysis

Methods of Correlation Analysis:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

- Pearson Product-Moment Correlation

  Limitation: Doesn't handle controls

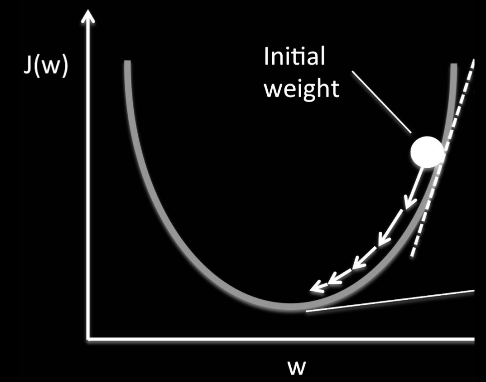
- Standardized Multivariate Linear Regression

  Fit the model: $$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_m X_{m1} + \epsilon_i$$

  Option 1: Gradient Descent:

  $J = \sum (y - \hat{y})^2$ -- "Sum of Squares" Error

  Option 2: Matrix model: $$Y = X\beta + \epsilon$$



Differential Language Analysis

Methods of Correlation Analysis:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

- Pearson Product-Moment Correlation

  Limitation: Doesn't handle controls

- Standardized Multivariate Linear Regression

  Fit the model:

  $$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_m X_{m1} + \epsilon_i$$

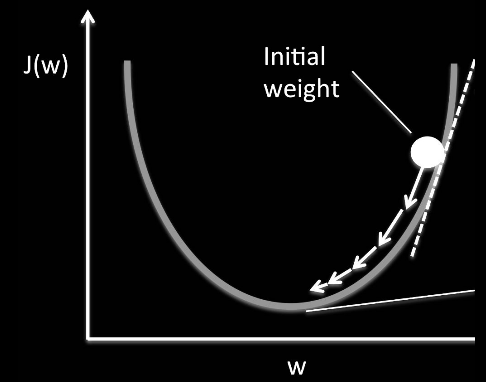
  Option 1: Gradient Descent:

  $J = \sum (y - \hat{y})^2$ -- "Sum of Squares" Error

  Option 2: Matrix model: $Y = X\beta + \epsilon$

  Matrix Computation Solution:

  $$\hat{\beta} = (X^T X)^{-1} X^T Y$$



Differential Language Analysis

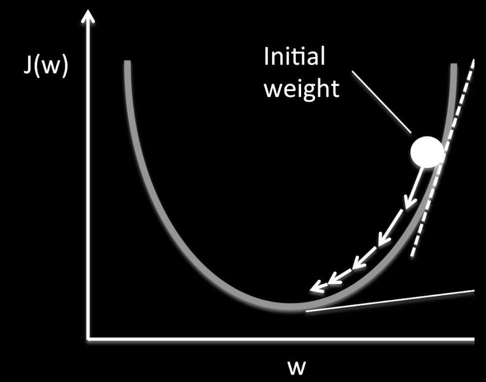
Methods of Correlation Analysis:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

- Pearson Product-Moment Correlation
  Limitation: Doesn't handle controls

- Standardized Multivariate Linear Regression
  Fit the model: $Y_i = \beta_0 + \boxed{\beta_1} X_{i1} + \beta_2 X_{i2} + \ldots + \beta_m X_{m1} + \epsilon_i$
  Option 1: Gradient Descent:
  $J = \sum (y - \hat{y})^2$ -- "Sum of Squares" Error
  Option 2: Matrix model: $Y = X\beta + \epsilon$
  Matrix Computation Solution:

$$\hat{\beta} = (X^T X)^{-1} X^T Y$$



Differential Language Analysis

Methods of “Correlation” Analysis for binary outcomes:

- Logistic Regression over Standardized variables

- Odds Ratio

$$\frac{\dfrac{\dfrac{countA(\text{"horrible"})}{NA}}{1-\dfrac{countA(\text{"horrible"})}{NA}}}{\dfrac{\dfrac{countB(\text{"horrible"})}{NB}}{1-\dfrac{countB(\text{"horrible"})}{NB}}}$$

Differential Language Analysis

Methods of “Correlation” Analysis for binary outcomes:

- Logistic Regression over Standardized variables

- Odds Ratio

$$\frac{\dfrac{\frac{countA(\text{"horrible"})}{NA}}{1-\frac{countA(\text{"horrible"})}{NA}}}{\dfrac{\frac{countB(\text{"horrible"})}{NB}}{1-\frac{countB(\text{"horrible"})}{NB}}} \propto log\left(\frac{\frac{countA(\text{"horrible"})}{NA}}{1-\frac{countA(\text{"horrible"})}{NA}}\right) - log\left(\frac{\frac{countB(\text{"horrible"})}{NB}}{1-\frac{countB(\text{"horrible"})}{NB}}\right)$$

Differential Language Analysis

Methods of "Correlation" Analysis for binary outcomes:

- Logistic Regression over Standardized variables
- Odds Ratio

$$\frac{\dfrac{\frac{countA(\text{"horrible"})}{NA}}{1-\frac{countA(\text{"horrible"})}{NA}}}{\dfrac{\frac{countB(\text{"horrible"})}{NB}}{1-\frac{countB(\text{"horrible"})}{NB}}} \propto log\left(\frac{\frac{countA(\text{"horrible"})}{NA}}{1-\frac{countA(\text{"horrible"})}{NA}}\right) - log\left(\frac{\frac{countB(\text{"horrible"})}{NB}}{1-\frac{countB(\text{"horrible"})}{NB}}\right)$$

$$= log\left(\frac{countA(\text{"horrible"})}{NA-countA(\text{"horrible"})}\right) - log\left(\frac{countB(\text{"horrible"})}{NB-countB(\text{"horrible"})}\right)$$

Differential Language Analysis

$$\log\left(\frac{countA(\text{"horrible"})}{NA-countA(\text{"horrible"})}\right)-\log\left(\frac{countB(\text{"horrible"})}{NB-countB(\text{"horrible"})}\right)$$

- Odds Ratio using Informative Dirichlet Prior

$$\delta_w^{(i-j)}=\log\left(\frac{f_w^i+\alpha_w}{n^i+\alpha_0-(f_w^i+\alpha_w)}\right)-\log\left(\frac{f_w^j+\alpha_w}{n^j+\alpha_0-(f_w^j+\alpha_w)}\right) \tag{20.9}$$

(Monroe et al., 2010; Jurafsky, 2017)

Differential Language Analysis

$$log\left(\frac{countA(\text{"horrible"})}{NA - countA(\text{"horrible"})}\right) - log\left(\frac{countB(\text{"horrible"})}{NB - countB(\text{"horrible"})}\right)$$

- Odds Ratio using **Informative Dirichlet Prior**

$$\delta_w^{(i-j)} = \log\left(\frac{f_w^i + \boxed{\alpha_w}}{n^i + \boxed{\alpha_0} - (f_w^i + \boxed{\alpha_w})}\right) - \log\left(\frac{f_w^j + \boxed{\alpha_w}}{n^j + \boxed{\alpha_0} - (f_w^j + \boxed{\alpha_w})}\right) \quad (20.9)$$

(where n^i is the size of corpus i, n^j is the size of corpus j, f_w^i is the count of word w in corpus i, f_w^j is the count of word w in corpus j, α_0 is the size of the background corpus, and α_w is the count of word w in the background corpus.)

(Monroe et al., 2010; Jurafsky, 2017)

Differential Language Analysis

$$log\left(\frac{countA(\text{“horrible”})}{NA - countA(\text{“horrible”})}\right) - log\left(\frac{countB(\text{“horrible”})}{NB - countB(\text{“horrible”})}\right)$$

- Odds Ratio using **Informative Dirichlet Prior**

$$\delta_w^{(i-j)} = \log\left(\frac{f_w^i + \boxed{\alpha_w}}{n^i + \boxed{\alpha_0} - (f_w^i + \boxed{\alpha_w})}\right) - \log\left(\frac{f_w^j + \boxed{\alpha_w}}{n^j + \boxed{\alpha_0} - (f_w^j + \boxed{\alpha_w})}\right) \quad (20.9)$$

(where n^i is the size of corpus i, n^j is the s … pus j, f_w^i is the count of word w in corpus i, f_w^j is the count of word w in … is the size of the background corpus, and α_w is the count of word w in … corpus.)

Bayesian term for “smoothing”: accounts for uncertainty as a function of event frequency (i.e. words observed less) by integrating “prior” beliefs mathematically.

(Mo

Differential Language Analysis

$$log\left(\frac{countA(\text{“horrible”})}{NA - countA(\text{“horrible”})}\right) - log\left(\frac{countB(\text{“horrible”})}{NB - countB(\text{“horrible”})}\right)$$

- Odds Ratio using **Informative Dirichlet Prior**

$$\delta_w^{(i-j)} = \log\left(\frac{f_w^i + \boxed{\alpha_w}}{n^i + \boxed{\alpha_0} - (f_w^i + \boxed{\alpha_w})}\right) - \log\left(\frac{f_w^j + \boxed{\alpha_w}}{n^j + \boxed{\alpha_0} - (f_w^j + \boxed{\alpha_w})}\right) \quad (20.9)$$

(where n^i is the size of corpus i, n^j is the s … pus j, f_w^i is the count of word w in corpus i, f_w^j is the count of word w in … is the size of the background corpus, and α_w is the count of word w in … l corpus.)

Bayesian term for “smoothing”: accounts for uncertainty as a function of event frequency (i.e. words observed less) by integrating “prior” beliefs mathematically.
“Informative”: the prior is based on past evidence. Here, the total frequency of the word.

(Mc

Differential Language Analysis

$$log\left(\frac{countA(\text{"horrible"})}{NA - countA(\text{"horrible"})}\right) - log\left(\frac{countB(\text{"horrible"})}{NB - countB(\text{"horrible"})}\right)$$

- Odds Ratio using Informative Dirichlet Prior

$$\delta_w^{(i-j)} = \log\left(\frac{f_w^i + \alpha_w}{n^i + \alpha_0 - (f_w^i + \alpha_w)}\right) - \log\left(\frac{f_w^j + \alpha_w}{n^j + \alpha_0 - (f_w^j + \alpha_w)}\right) \qquad (20.9)$$

(where n^i is the size of corpus i, n^j is the size of corpus j, f_w^i is the count of word w in corpus i, f_w^j is the count of word w in corpus j, α_0 is the size of the background corpus, and α_w is the count of word w in the background corpus.)

(Monroe et al., 2010; Jurafsky, 2017)

Differential Language Analysis

$$log\left(\frac{countA(\text{"horrible"})}{NA-countA(\text{"horrible"})}\right) - log\left(\frac{countB(\text{"horrible"})}{NB-countB(\text{"horrible"})}\right)$$

- Odds Ratio using Informative Dirichlet Prior

$$\delta_w^{(i-j)} = \log\left(\frac{f_w^i + \alpha_w}{n^i + \alpha_0 - (f_w^i + \alpha_w)}\right) - \log\left(\frac{f_w^j + \alpha_w}{n^j + \alpha_0 - (f_w^j + \alpha_w)}\right) \quad (20.9)$$

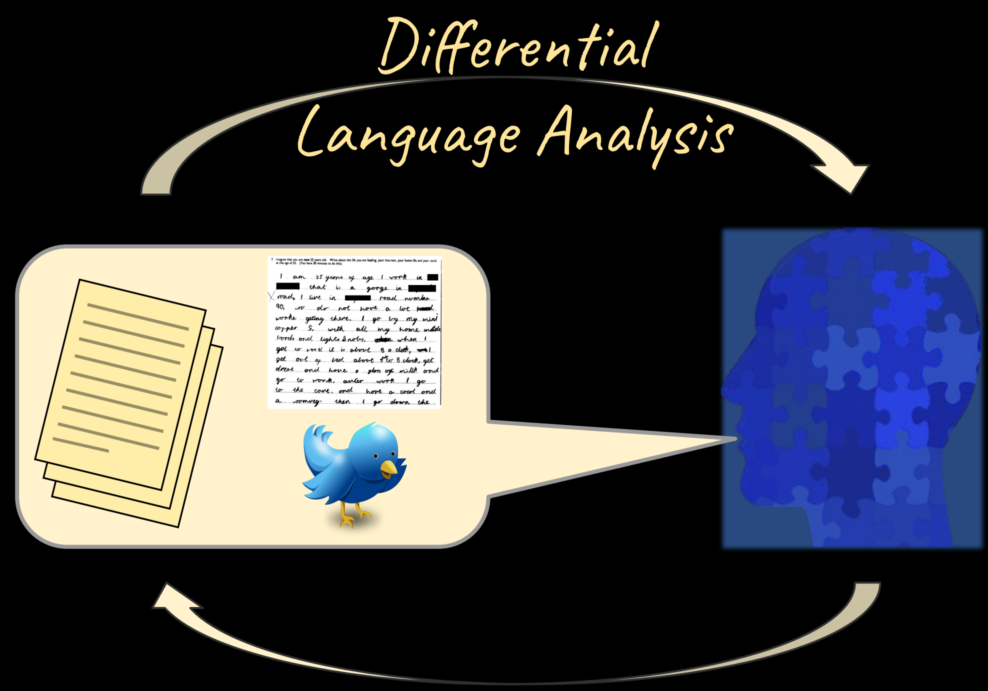
(where n^i is the size of corpus i, n^j is the size of corpus j, f_w^i is the count of word w in corpus i, f_w^j is the count of word w in corpus j, α_0 is the size of the background corpus, and α_w is the count of word w in the background corpus.)

Final score is standardized (z-scored): $\dfrac{\hat{\delta}_w^{(i-j)}}{\sqrt{\sigma^2\left(\hat{\delta}_w^{(i-j)}\right)}}$, where

$$\sigma^2\left(\hat{\delta}_w^{(i-j)}\right) \approx \frac{1}{f_w^i + \alpha_w} + \frac{1}{f_w^j + \alpha_w}$$

(Monroe et al., 2010; Jurafsky, 2017)

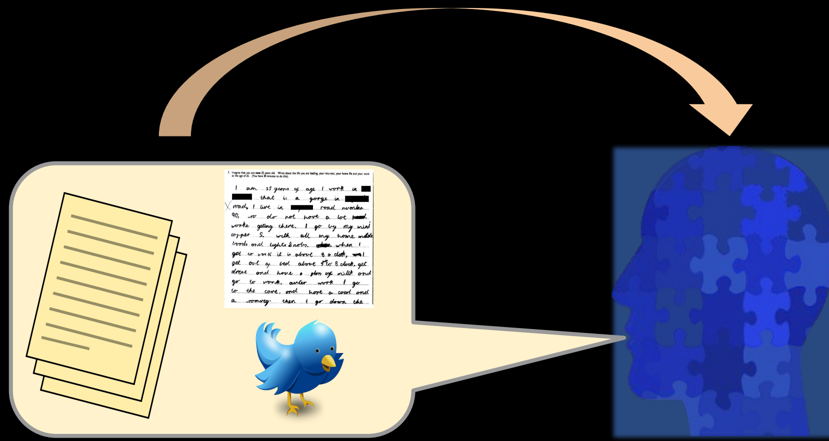
Python Library, CLI, and Colab for DLA



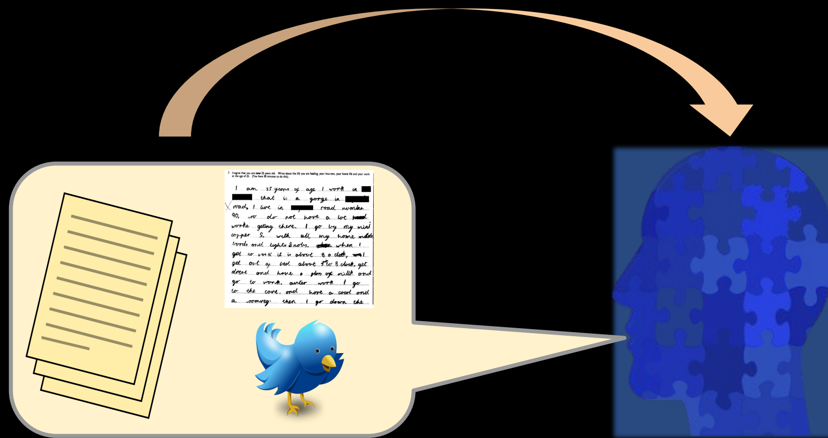
https://dlatk.github.io/

Getting Started in Colab

Natural language is generated by people.



Natural language is generated by people.



Shannon, 1948

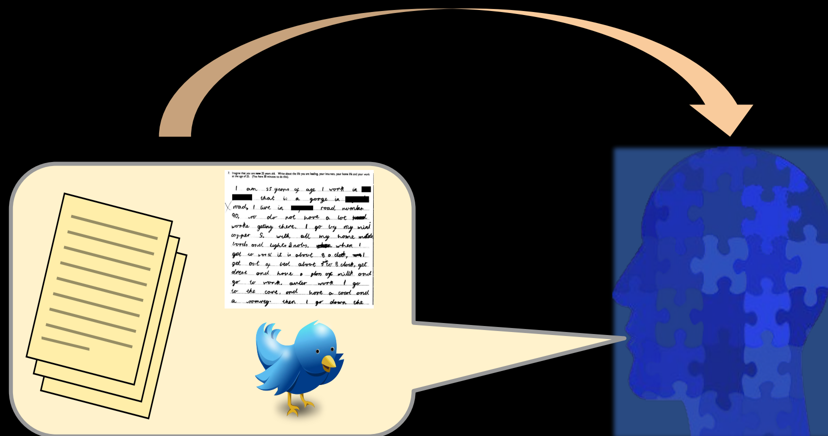
Mosteller & Wallace 1963

Clark & Schober, 1992

Mairesse, Walker, et al., 2007

Hovy & Soogaard, 2015

Natural language is generated by people.



"The common misconception is that language has got to do with words and what they mean. It does not. It has to do with people and what they mean."

Shannon, 1948

Mosteller & Wallace 1963

Clark & Schober, 1992

Mairesse, Walker, et al., 2007

Hovy & Soogaard, 2015

Human-Centered NLP – We will cover:

1. Differential Language Analysis
2. Human Factor Adaptation
3. Human Language Modeling

Human-Centered NLP – We will cover:

1. Differential Language Analysis
2. **Human Factor Adaptation**
3. Human Language Modeling

Approaches to Human Factor Inclusion

1. **Bias Mitigation:** Optimize so as not to pick up on unwanted relationships.

   (e.g. image captioner label pictures of men in kitchen as women)

Approaches to Human Factor Inclusion

1. **Bias Mitigation:** Optimize so as not to pick up on unwanted relationships.

   (e.g. image captioner label pictures of men in kitchen as women)

2. **Additive:** Include direct effect of human factor on outcome.

   (e.g. age and distinguishing PTSD from Depression; covariate in regression)

Approaches to Human Factor Inclusion

1. **Bias Mitigation:** Optimize so as not to pick up on unwanted relationships.

   (e.g. image captioner label pictures of men in kitchen as women)

2. **Additive:** Include direct effect of human factor on outcome.

   (e.g. age and distinguishing PTSD from Depression)

3. **Adaptive:** Allow meaning if language to change depending on human context. (also called “compositional”)

   ?

   (e.g. “sick” said from a young individual versus old individual)

Approaches to Human Factor Inclusion

1. **Bias Mitigation:** Opti so as not to pick up on

   What are human “factors”?

   in kitchen as women)

2. **Additive:** Include direct effect of human factor on outcome.
   (e.g. age and distinguishing PTSD from Depression)

3. **Adaptive:** Allow meaning if language to change depending on human context. (also called “compositional”)
   ?
   (e.g. “sick” said from a young individual versus old individual)

Human Factors

--- Any attribute, represented as a continuous or discrete variable, of the humans generating the natural language.

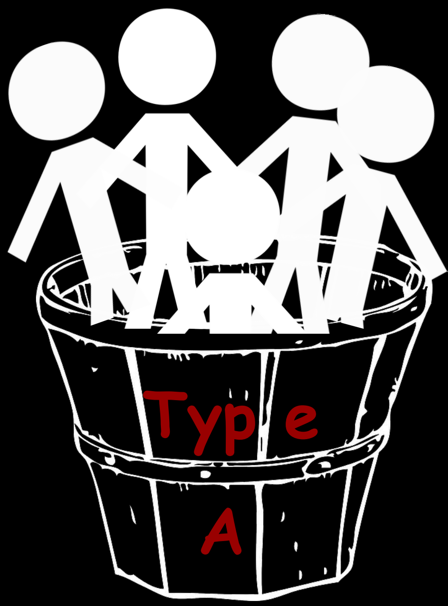
E.g.

- Gender
- Age
- Personality
- Ethnicity
- Socio-economic status

Human Factors

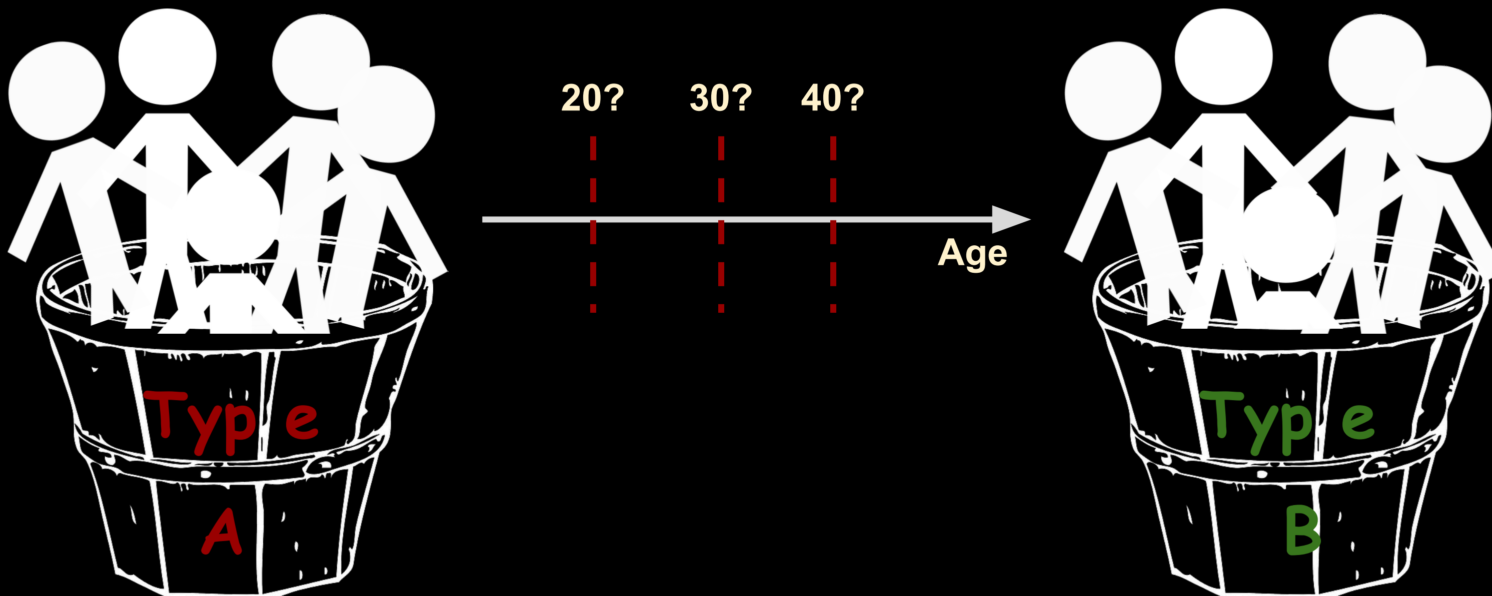
typically requires putting people into discrete bins *"most latent variables of interest to psychiatrists and personality and clinical psychologists are dimensional [continuous]"*

(Haslam et al., 2012)



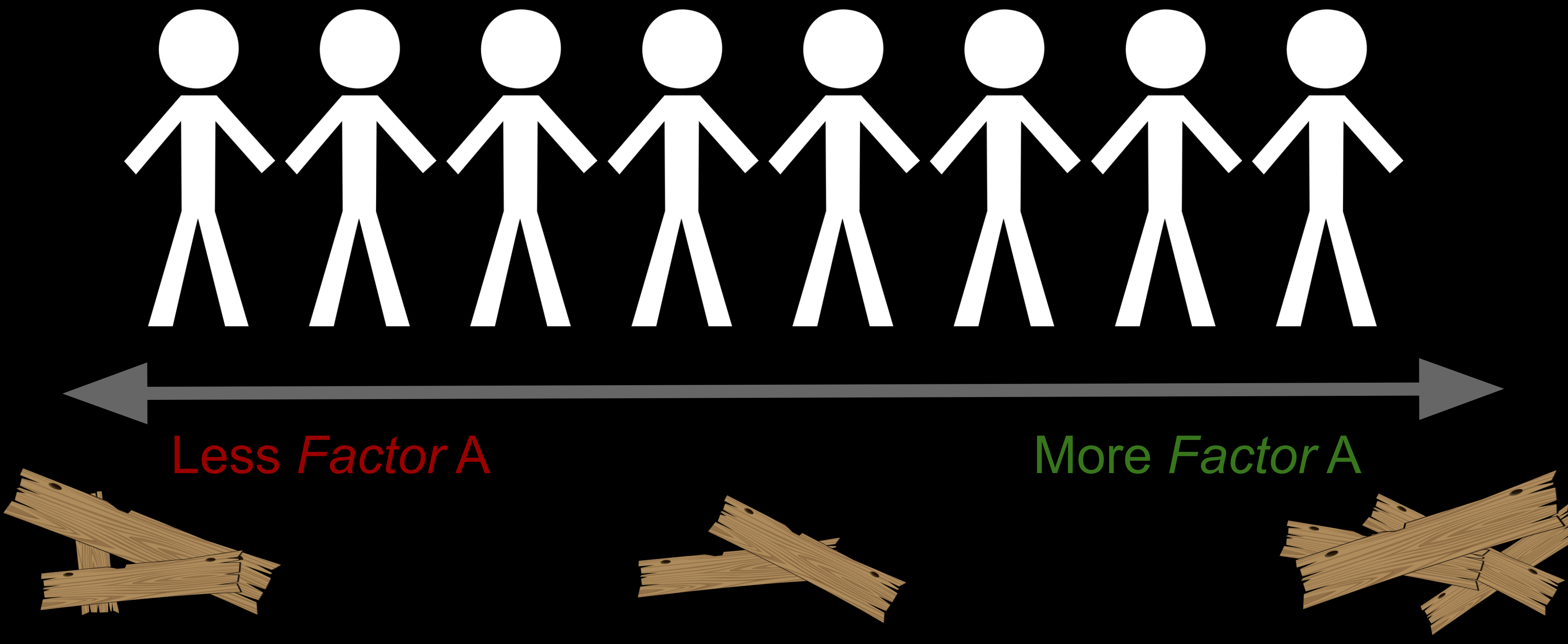
"most latent variables of interest to psychiatrists and personality and clinical psychologists are dimensional [continuous]"

(Haslam et al., 2012)



“most latent variables of interest to psychiatrists and personality and clinical psychologists are dimensional [continuous]”

(Haslam et al., 2012)



Adaptation Approach: Domain Adaptation

Features for: source target

$$\Phi^s(x) = \langle x, x, \mathbf{0} \rangle, \quad \Phi^t(x) = \langle x, \mathbf{0}, x \rangle$$

Frustratingly Easy Domain Adaptation

Hal Daumé III
School of Computing
University of Utah
Salt Lake City, Utah 84112
me@hal3.name

Abstract

We describe an approach to domain adapta-
tion that is appropriate exactly in the case

supervised case. The fully supervised case mod-
els the following scenario. We have access to a
large, annotated corpus of data

Adaptation Approach: Domain Adaptation

Features for: source target

$$\Phi^s(x) = \langle x, x, \mathbf{0} \rangle, \quad \Phi^t(x) = \langle x, \mathbf{0}, x \rangle$$

```
newX = []
for all x in source_x:
  newX.append(x + x + [0]*len(x))
for all x in target_x:
  newX.append(x + [0]*len(x), x)
```

Frustratingly Easy Domain Adaptation

Hal Daumé III
School of Computing
University of Utah
Salt Lake City, Utah 84112
me@hal3.name

Abstract

We describe an approach to domain adapta-
tion that is appropriate exactly in the case

supervised case. The fully supervised case mod-
els the following scenario. We have access to a
large, annotated corpus of data fro

Adaptation Approach: Domain Adaptation

Features for: source target

$$\Phi^s(\boldsymbol{x}) = \langle \boldsymbol{x}, \boldsymbol{x}, \boldsymbol{0} \rangle, \quad \Phi^t(\boldsymbol{x}) = \langle \boldsymbol{x}, \boldsymbol{0}, \boldsymbol{x} \rangle$$

```
newX = []
for all x in source_x:
  newX.append(x + x + [0]*len(x))
for all x in target_x
  newX.append(x + [0]*len(x), x)

newY = source_y + target_y

model = model.train(newX,newY)
```

Adaptation Approach: Factor Adaptation

Human Centered NLP with User-Factor Adaptation

Veronica E. Lynn, Youngseo Son, Vivek Kulkarni
Niranjan Balasubramanian and **H. Andrew Schwartz**
Stony Brook University
Stony Brook, NY
{velynn, yson, vvkulkarni, niranjan, has}@cs.stonybrook.edu

Abstract

We pose the general task of *user-factor adaptation* — adapting supervised learning models to real-valued user factors in-

and Costa Jr., 1989; Ruscio and Ruscio, 2000; Widiger and Samuel, 2005).

Here, we ask how one can adapt NLP models to real-valued human *factors* – continuous valued attributes that capture fine-grained differences be-

Residualized Factor Adaptation for Community Social Media Prediction Tasks

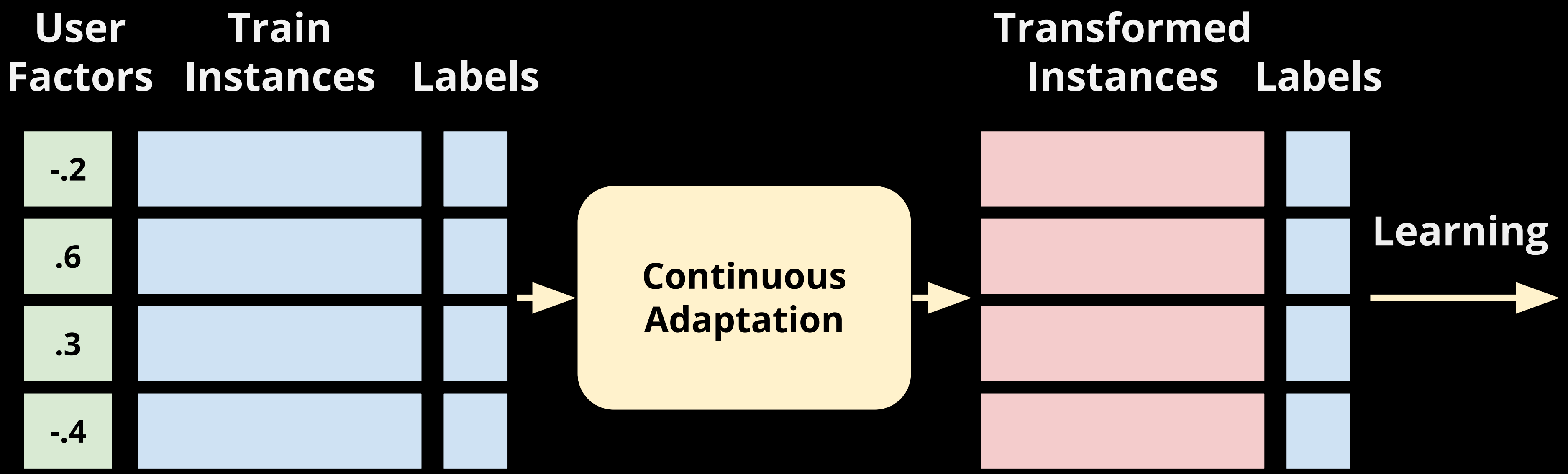
Mohammadzaman Zamani,[1] **H. Andrew Schwartz,**[1] **Veronica E. Lynn,**[1]
Salvatore Giorgi,[2] and **Niranjan Balasubramanian**[1]
[1] Computer Science Department, Stony Brook University
[2]Department of Psychology, University of Pennsylvania
mzamani@cs.stonybrook.edu

Abstract

Predictive models over social media language

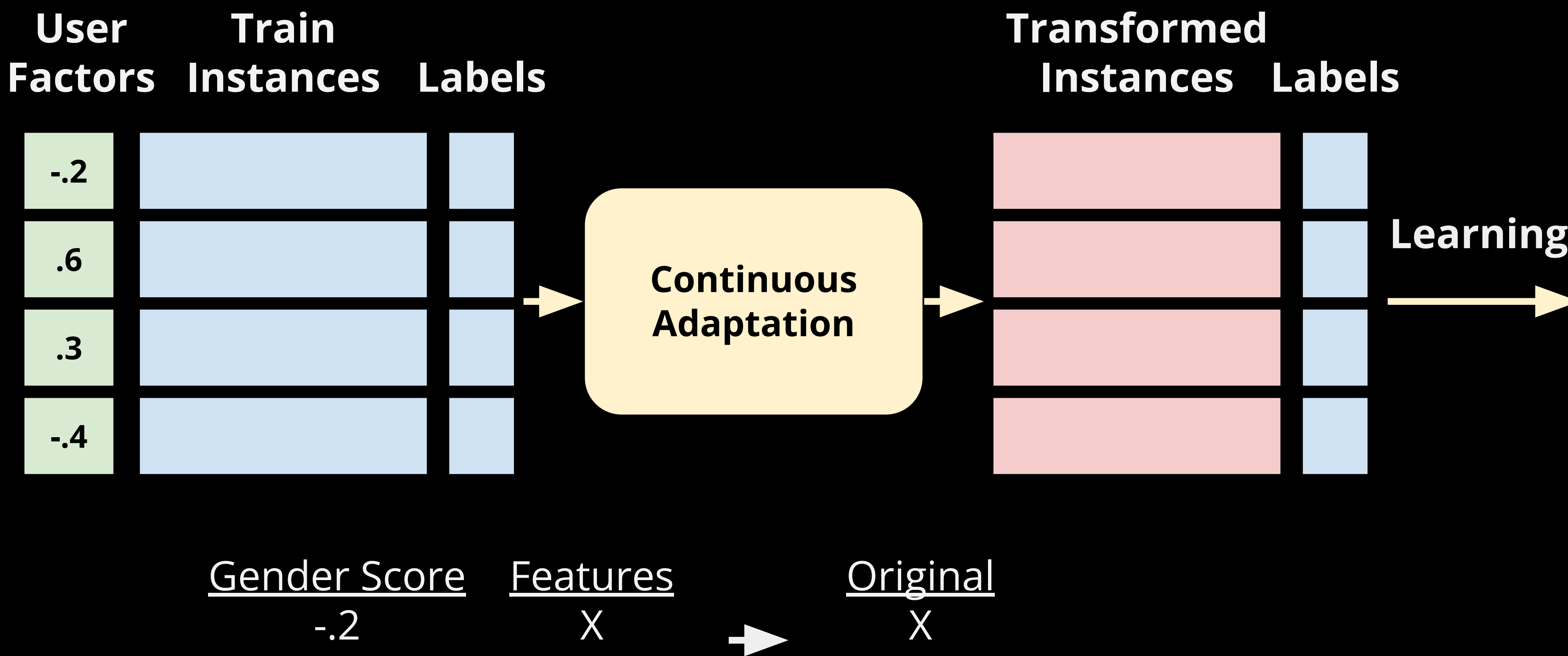
linked to socio-demographic factors (age, gender, race, education, income levels) with many social scientific studies supporting their predictive

Our Method: Continuous Adaptation



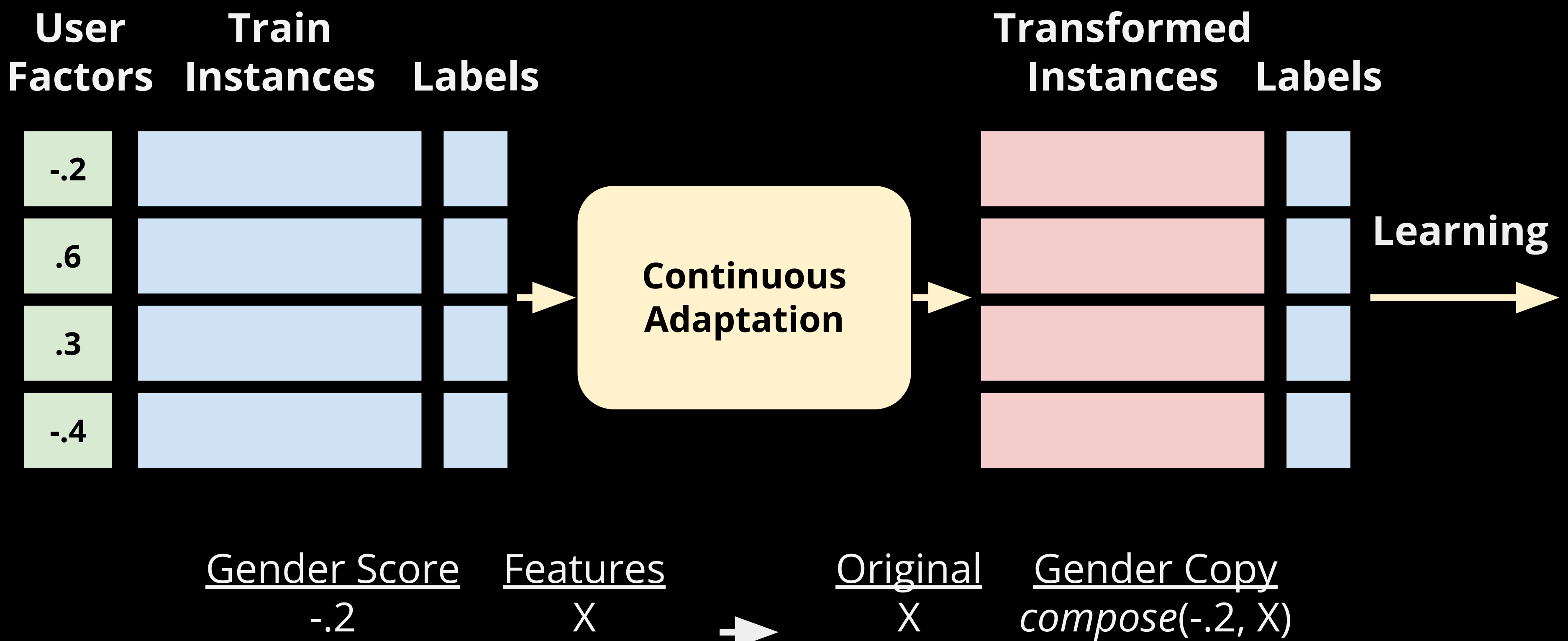
(Lynn et al., 2017)

Our Method: Continuous Adaptation



(Lynn et al., 2017)

Our Method: Continuous Adaptation



(Lynn et al., 2017)

User Factor Adaptation: Handling multiple factors

Replicate features for each factor:

A compositional function c combines d user factor scores $f_{u,d}$ with original feature values $\mathbf{x}$:

$$\Phi(\mathbf{x}, u) = \langle \mathbf{x}, c(f_{u,1}, \mathbf{x}), c(f_{u,2}, \mathbf{x}), \cdots, c(f_{u,d}, \mathbf{x}) \rangle$$

(Lynn et al., 2017)

User Factor Adaptation: Handling multiple factors

Replicate features for each factor:

A compositional function c combines d user factor scores $f_{u,d}$ with original feature values $\mathbf{x}$:

$$\Phi(\mathbf{x}, u) = \langle \mathbf{x}, c(f_{u,1}, \mathbf{x}), c(f_{u,2}, \mathbf{x}), \cdots, c(f_{u,d}, \mathbf{x}) \rangle$$

User	Factor Classes	Augmented Instance $\Phi(\mathbf{x}, u)$
User 1	F_1	$\langle \mathbf{x}, \mathbf{x}, \mathbf{0}, \mathbf{0}, \cdots, 0 \rangle$
User 2	F_2	$\langle \mathbf{x}, \mathbf{0}, \mathbf{x}, \mathbf{0}, \cdots, 0 \rangle$
User 3	F_1, F_3	$\langle \mathbf{x}, \mathbf{x}, \mathbf{0}, \mathbf{x}, \cdots, 0 \rangle$
User 4	F_k	$\langle \mathbf{x}, \mathbf{0}, \mathbf{0}, \cdots, 0, \mathrm{x} \rangle$

Table 1: Discrete Factor Adaptation: Augmentations of an original instance vector $\mathbf{x}$ under different factor class mappings. With k domains the augmented feature vector is of length $n(k+1)$.

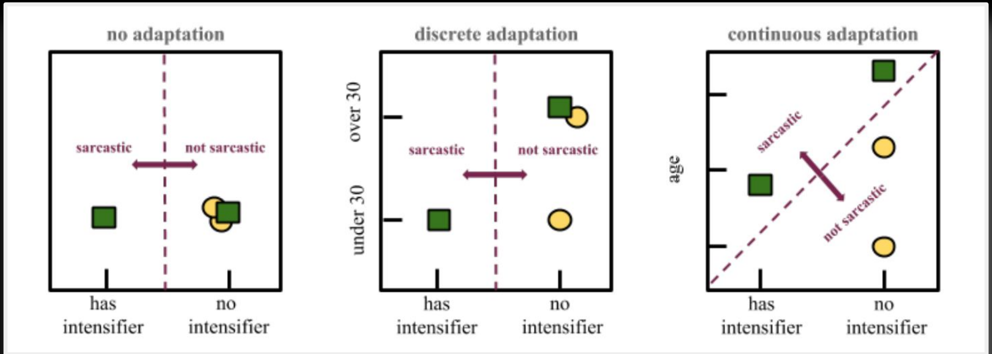
(Lynn et al., 2017)

User Factor Adaptation: Handling multiple factors

Replicate features for each factor:

A compositional function c combines d user factor scores $f_{u,d}$ with original feature values $\mathbf{x}$:

$$\Phi(\mathbf{x}, u) = \langle \mathbf{x}, c(f_{u,1}, \mathbf{x}), c(f_{u,2}, \mathbf{x}), \cdots, c(f_{u,d}, \mathbf{x}) \rangle$$



User	Factor Classes	Augmented Instance $\Phi(\mathbf{x}, u)$
User 1	F_1	$\langle \mathbf{x}, \mathbf{x}, \mathbf{0}, \mathbf{0}, \cdots, \mathbf{0} \rangle$
User 2	F_2	$\langle \mathbf{x}, \mathbf{0}, \mathbf{x}, \mathbf{0}, \cdots, \mathbf{0} \rangle$
User 3	F_1, F_3	$\langle \mathbf{x}, \mathbf{x}, \mathbf{0}, \mathbf{x}, \cdots, \mathbf{0} \rangle$
User 4	F_k	$\langle \mathbf{x}, \mathbf{0}, \mathbf{0}, \cdots, \mathbf{0}, \mathrm{x} \rangle$

Table 1: Discrete Factor Adaptation: Augmentations of an original instance vector $\mathbf{x}$ under different factor class mappings. With k domains the augmented feature vector is of length $n(k+1)$.

(Lynn et al., 2017)

Main Results

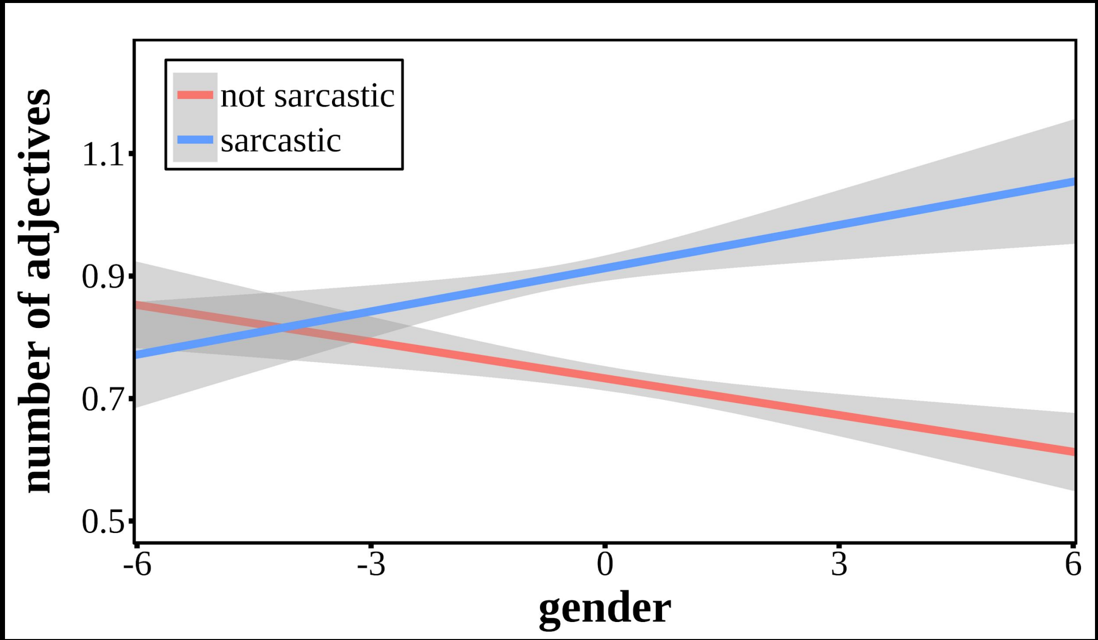
Adaptation improves over unadapted baselines (Lynn et al., 2017)

Task	**Metric**	**No Adaptation**	**Gender**	**Personality**	**Latent (User Embed)**
Stance	F1	64.9	**65.1 (+0.2)**	**66.3 (+1.4)**	**67.9 (+3.0)**
Sarcasm	F1	73.9	**75.1 (+1.2)**	**75.6 (+1.7)**	**77.3 (+3.4)**
Sentiment	Acc.	60.6	**61.0 (+0.4)**	**61.2 (+0.6)**	**60.7 (+0.1)**
PP-Attach	Acc.	71.0	70.7 (-0.3)	70.2 (-0.8)	70.8 (-0.2)
POS	Acc.	91.7	**91.9 (+0.2)**	91.2 (-0.5)	90.9 (-0.8)

Example: How Adaptation Helps

<u>Women</u>
more adjectives→sarcasm

<u>Men</u>
more adjectives→no sarcasm



more “male” **more “female”**

Problem

User factors are not always available.

Solution: User Factor Inference

<u>**past tweets**</u>

inferred factors

<u>**Known**</u>

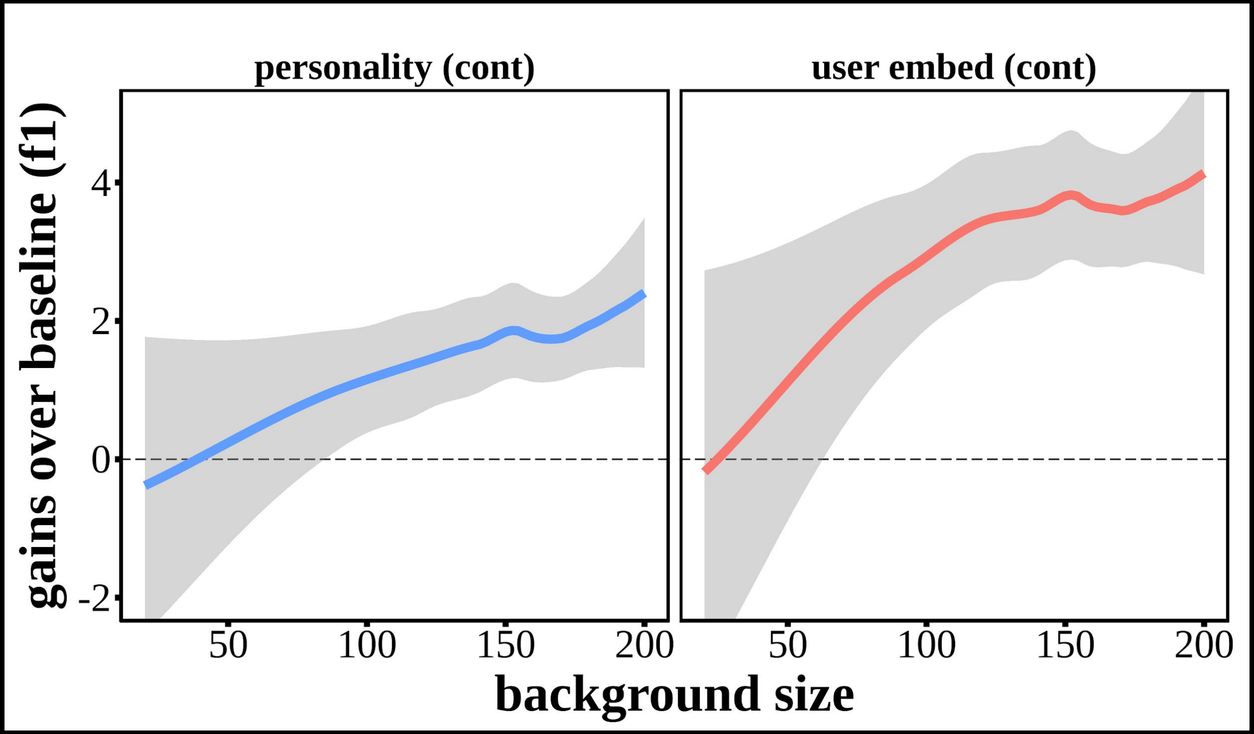
Age (Sap et al. 2014)
Gender (Sap et al. 2014)
Personality (Park et al. 2015)

<u>**Latent**</u>

User Embeddings
(Kulkarni et al. 2017)
Word2Vec
TF-IDF

Background Size

Using more background tweets to infer factors produces larger gains



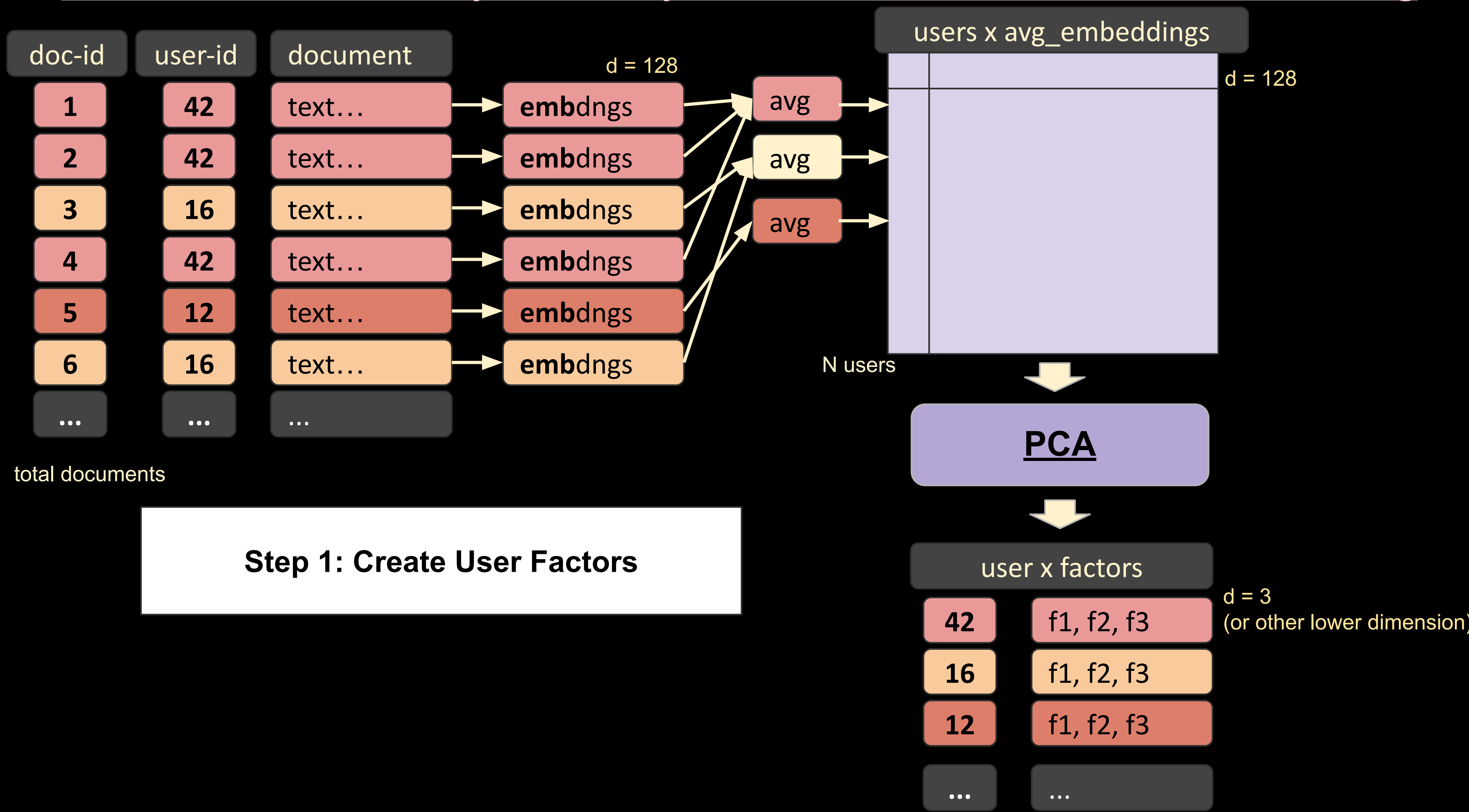
Full User Factors Adaptation Pipeline: with latent factors from training

d = 128

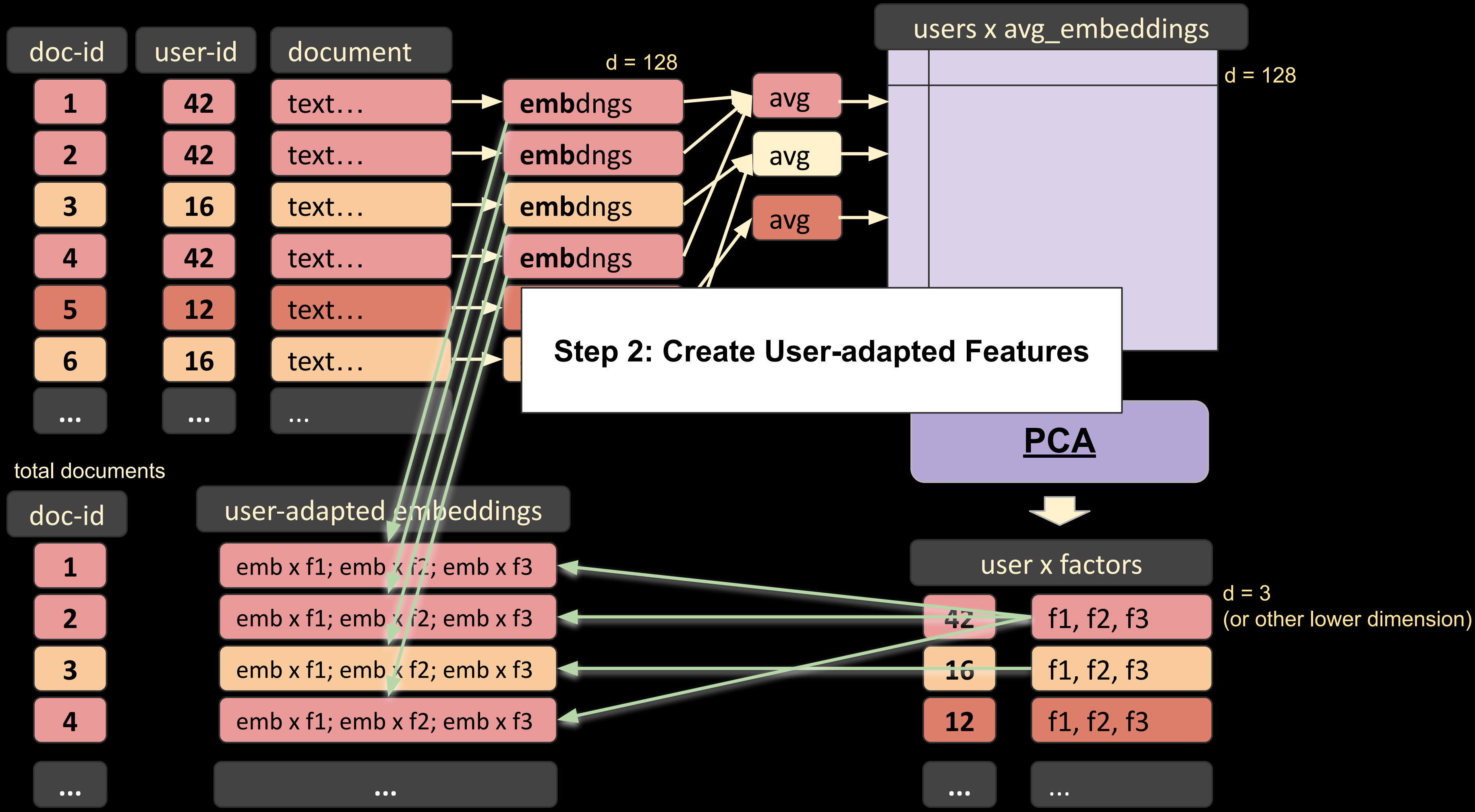
doc-id	user-id	document	
1	42	text…	embdngs
2	42	text…	embdngs
3	16	text…	embdngs
4	42	text…	embdngs
5	12	text…	embdngs
6	16	text…	embdngs
…	…	…	

total documents

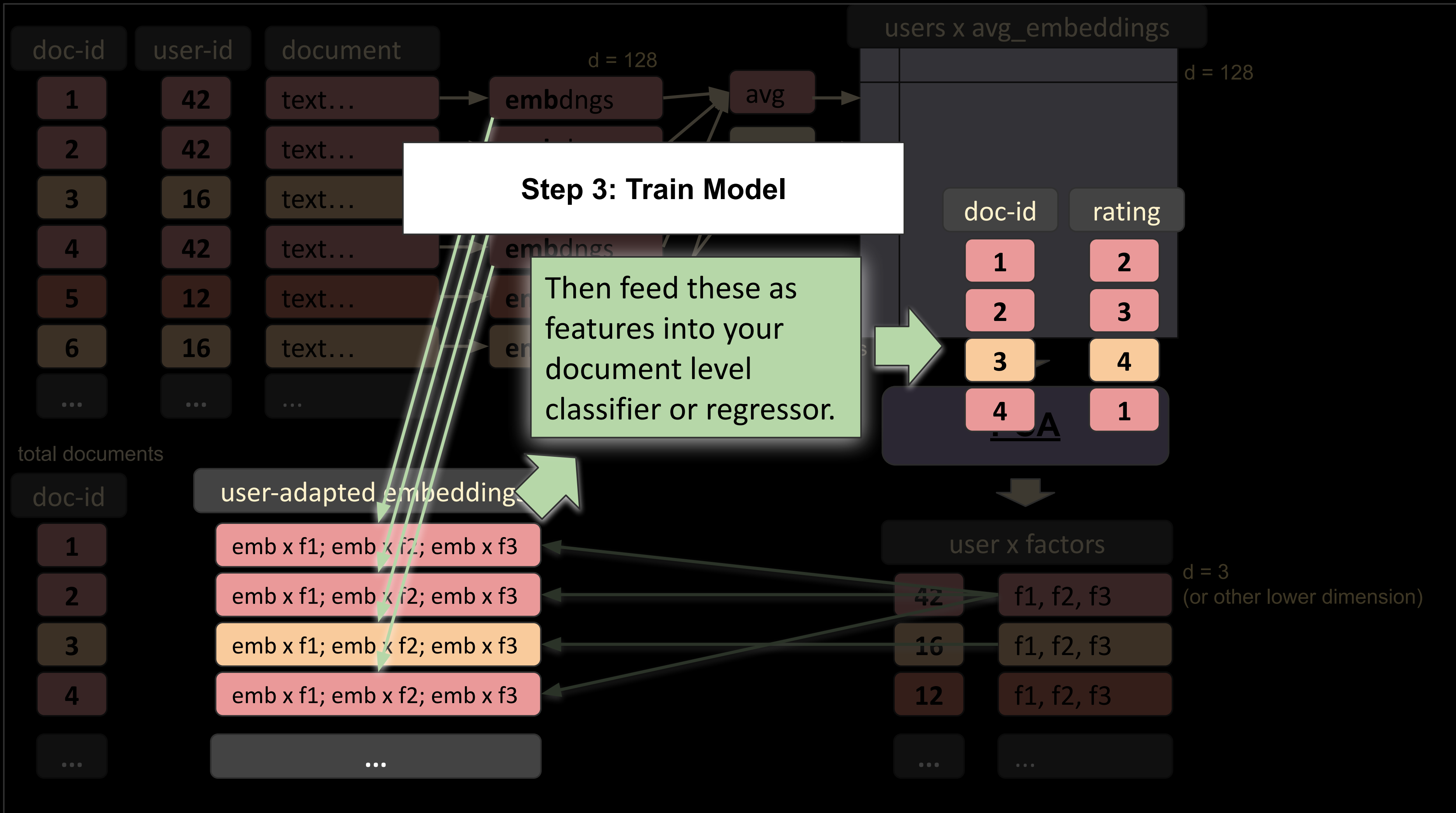
Full User Factors Adaptation Pipeline: with latent factors from training



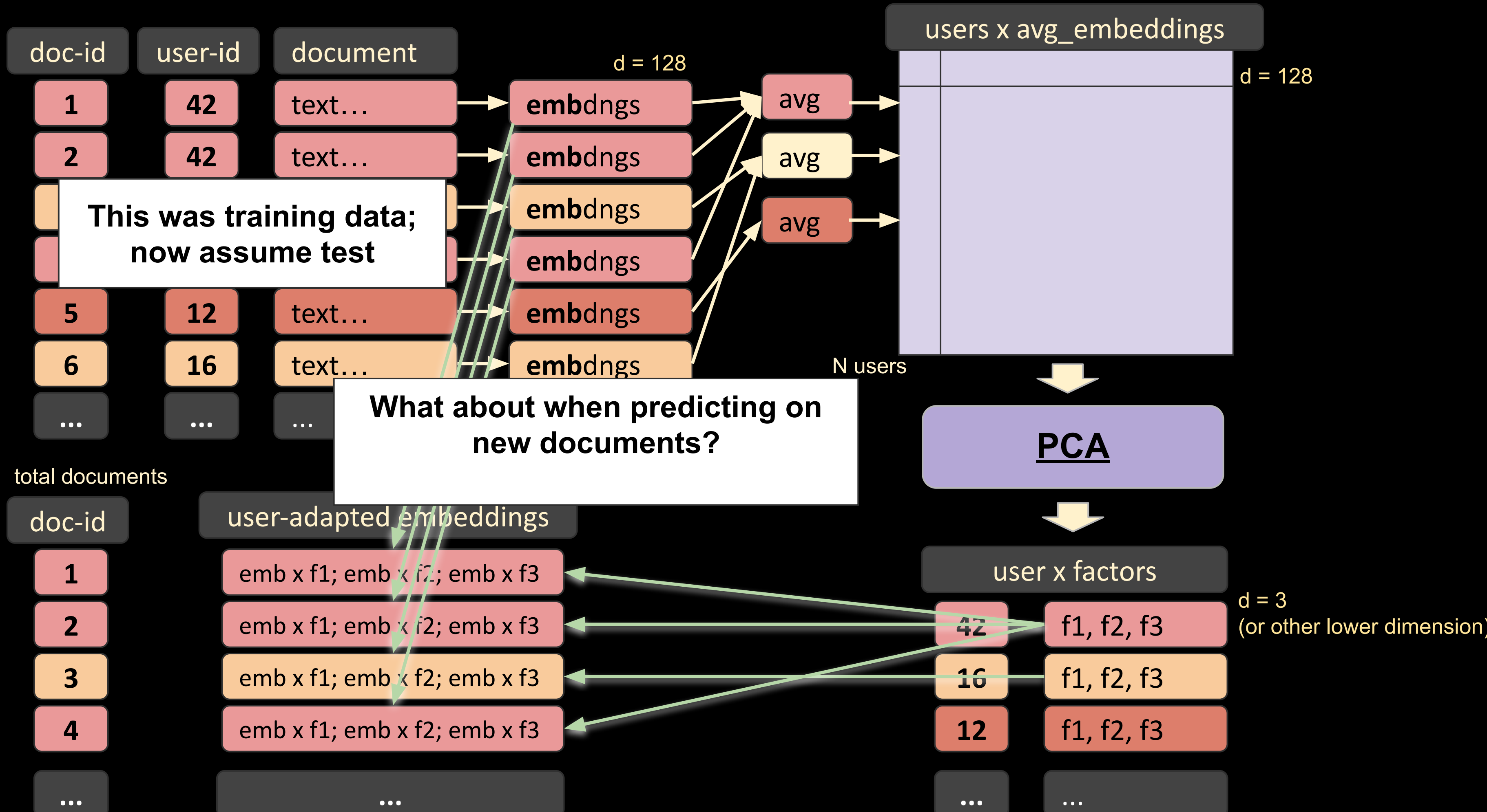
Full User Factors Adaptation Pipeline: with latent factors from training



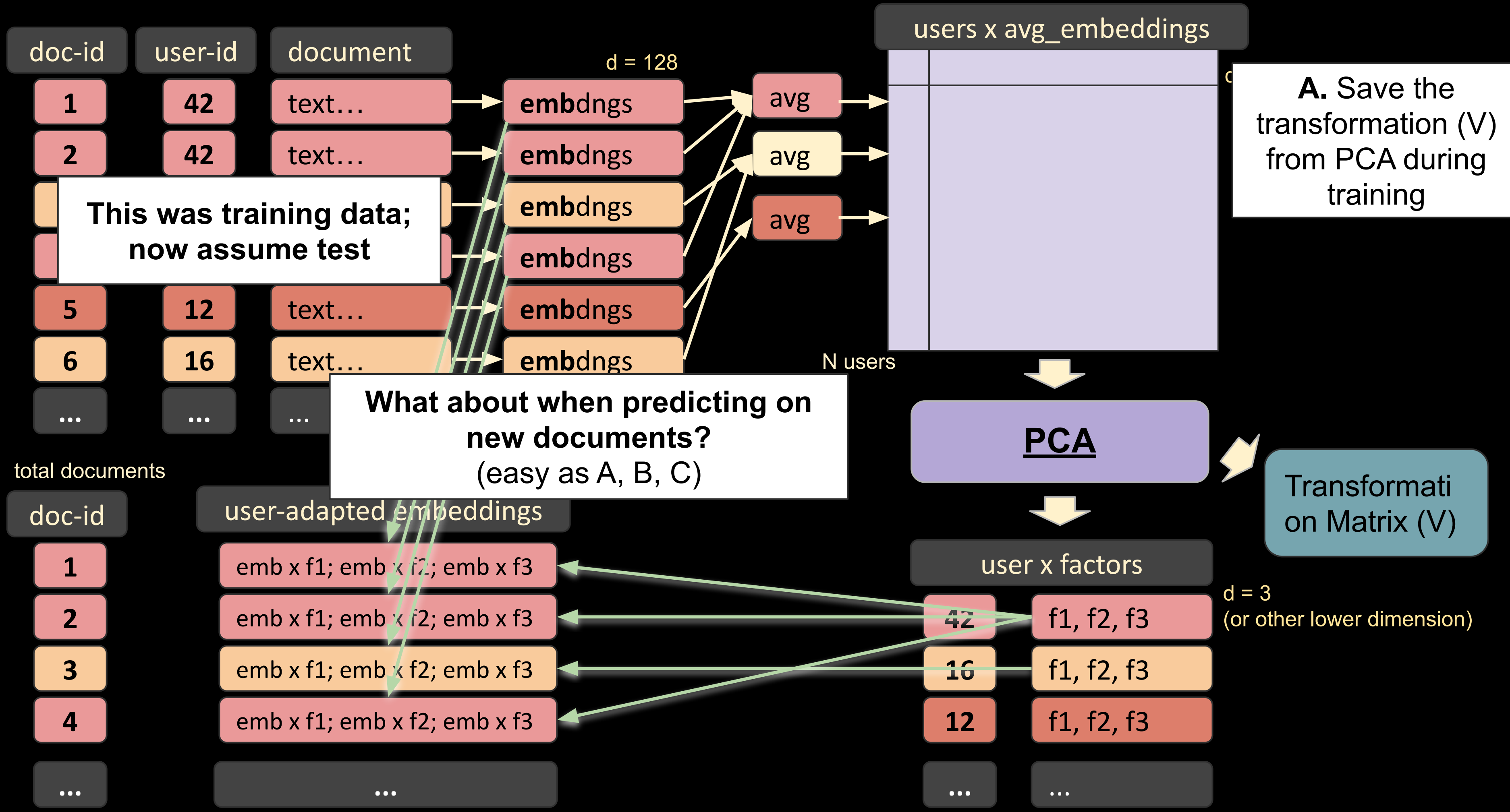
Full User Factors Adaptation Pipeline: with latent factors from training



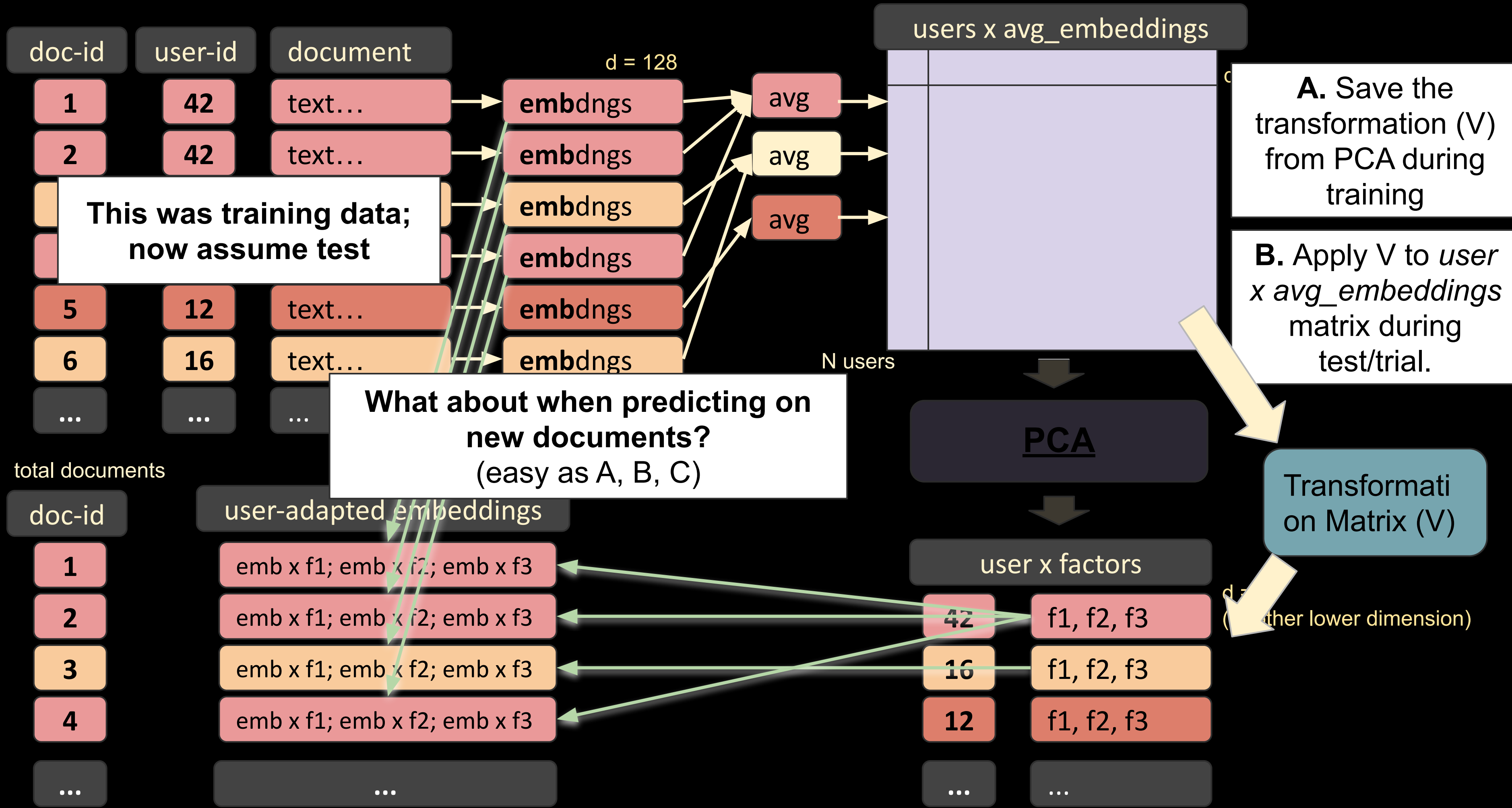
Full User Factors Adaptation Pipeline: with latent factors from training



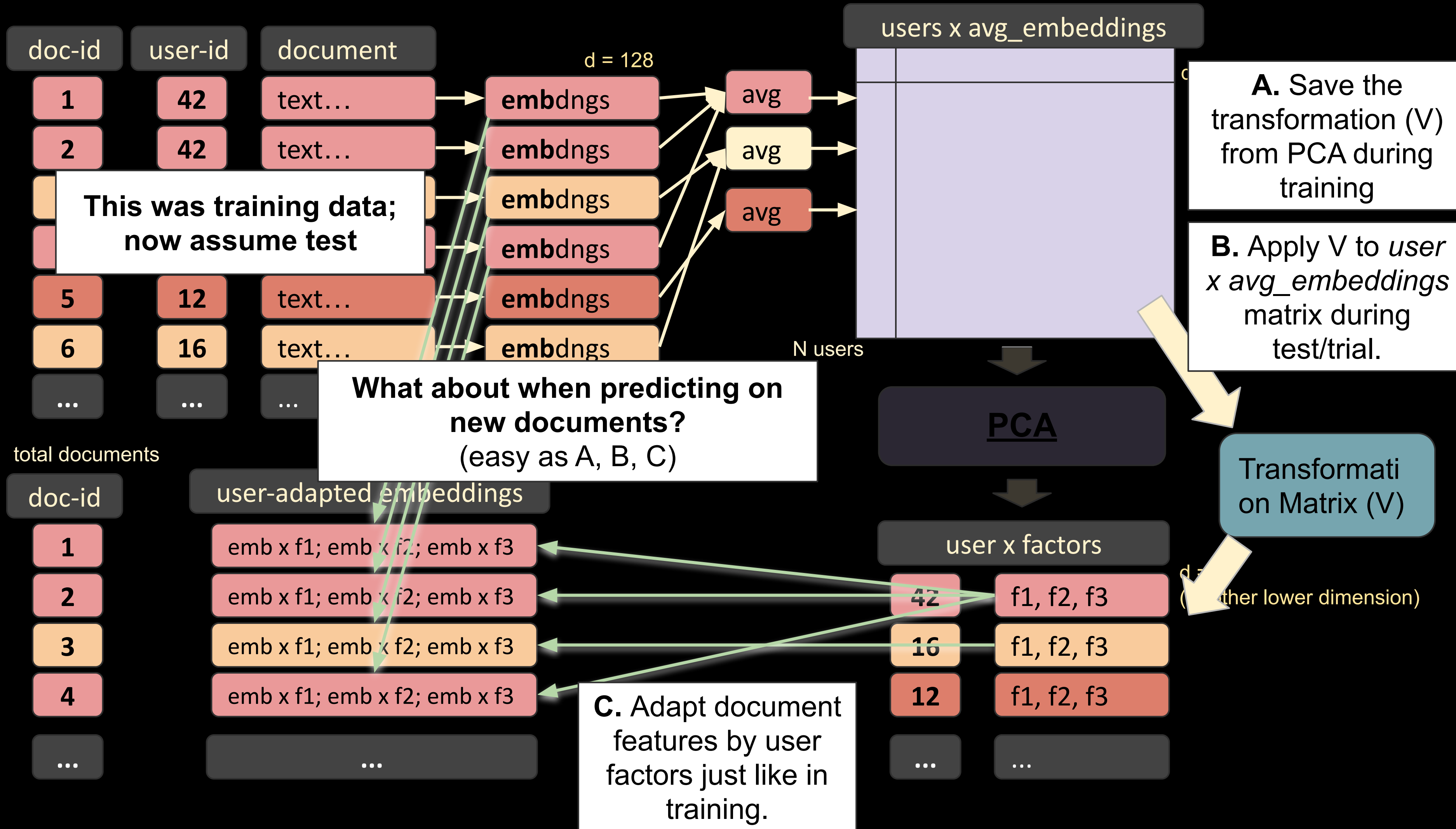
Full User Factors Adaptation Pipeline: with latent factors from training



Full User Factors Adaptation Pipeline: with latent factors from training



Full User Factors Adaptation Pipeline: with latent factors from training



Approaches to **Human Factor** Inclusion

1. **Bias Mitigation:** Opti… so as not to pick up on

   What are human “factors”?

   (e.g. image captioner label pictures of men in kitchen as women)

2. **Additive:** Include direct effect of human factor on outcome.
   (e.g. age and distinguishing PTSD from Depression)

3. **Adaptive:** Allow meaning if language to change depending on human context. (also called “compositional”)
   (e.g. “sick” said from a young individual versus old individual)

Approaches to **Human Factor** Inclusion

What are human “factors”?

1. **Bias Mitigation:** Opti so as not to pick up on
   (e.g. image captioner label pictures of men in kitchen as women)

2. **Additive:** Include direct effect of human factor on outcome.
   (e.g. age and distinguishing PTSD from Depression)

3. **Adaptive:** Allow meaning if language to change depending on human context. (also called “compositional”)
   (e.g. “sick” said from a young individual versus old individual)

Human-Centered NLP – We will cover:

1. Differential Language Analysis
2. **Human Factor Adaptation**
3. Human Language Modeling

Human-Centered NLP – We will cover:

1. Differential Language Analysis
2. Human Factor Adaptation
3. **Human Language Modeling**