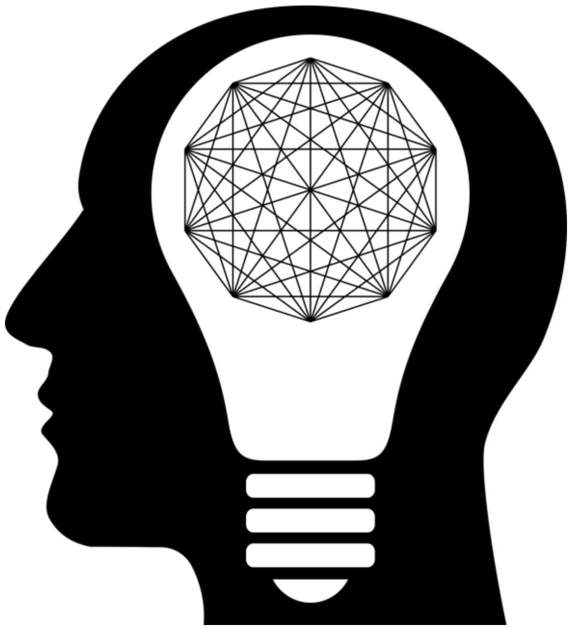
When do Words Matter ?

Understanding the impact of lexical choice on audience perception using Individual Treatment Effect Estimation

Motivation

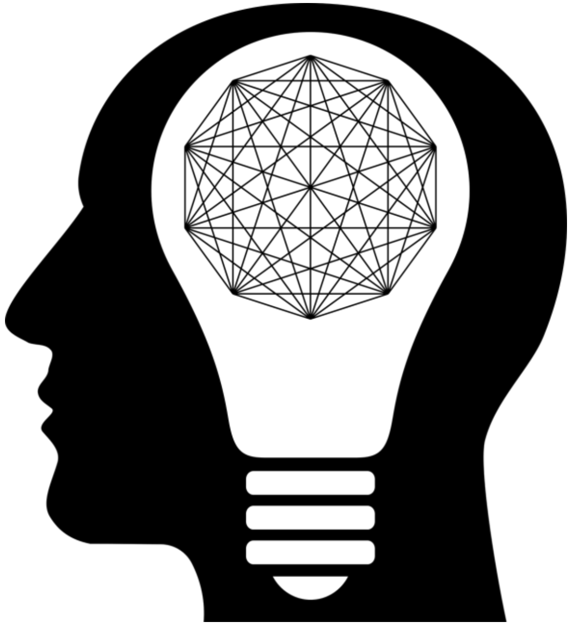
- A gift for my *wife*.



- A gift for my *husband*.

Motivation

- Plenty of *shops* nearby.



- Plenty of *boutiques* nearby.

Causal Effect of lexical choice on audience perception

- Single linguistic change
- Perception of one sentence

Related work

- Wording effect
    - *Message propagation*
    - *Memorability of movie quotes*
    - *Story sharing rates*
    - *User attribute*
    - *Human perception*
    - *Gender obfuscation*

- Causal inference (Individual Treatment Effect estimation)
    - *Drug use on health (medical)*
    - *Lexical choice on perception*

Concepts

ITE → LSE

- ITE: Individual Treatment Effect estimation
- LSE: Lexical Substitution Effect estimation

ITE: *Individual Treatment Effect estimation*

$$D = \{(\mathbf{X}_1, T_1, Y_1), \ldots, (\mathbf{X}_n, T_n, Y_n)\}$$

- X : covariate vector (e.g., *gender, age, height*)
- T : treatment indicator, $T_i \in \{0,1\}$
  - $T_i = 0$ $control\ group$, $T_i = 1$ $treatment\ group$
  - E.g., *patient did or did not take the drug*
- Y : observed outcome

- **Fundamental problem**: can only observe one outcome per individual

Strongly Ignorable Treatment Assignment (SITA):

$$T \perp \{Y^{(0)}, Y^{(1)}\} \mid \mathbf{X}$$

$$\tau(\mathbf{x}) = \mathbb{E}[Y^{(1)} | \mathbf{X} = \mathbf{x}] - \mathbb{E}[Y^{(0)} | \mathbf{X} = \mathbf{x}]$$

$$\hat{\tau}(\mathbf{x}) = \mathbb{E}[Y | T = 1, \mathbf{X} = \mathbf{x}] - \mathbb{E}[Y | T = 0, \mathbf{X} = \mathbf{x}]$$
$$= \frac{1}{|S_1(\mathbf{x})|} \sum_{i \in S_1(\mathbf{x})} Y_i - \frac{1}{|S_0(\mathbf{x})|} \sum_{i \in S_0(\mathbf{x})} Y_i$$

LSE: *Lexical Substitution Effect estimation*

$$D = \{(\mathbf{X}_1, T_1, Y_1), \ldots, (\mathbf{X}_n, T_n, Y_n)\}$$

- Unit of analysis: sentence
- X : covariate vector
  - e.g., *the other words in the sentence, excluding the one being substituted*
- T^P : lexical substitution assignment
  - P *: substitutable word pair, e.g., (shops, boutiques)*
  - $T^P = 0$ *control word*, $T^P = 1$ *treated by substituting control word to treatment word*.
  - E.g., *patient did or did not take the drug*
- Y : perception with respect to a particular attribute

$$\hat{\tau}(\mathbf{x}, p) = \frac{1}{|S_1^p(\mathbf{x})|} \sum_{i \in S_1^p(\mathbf{x})} Y_i - \frac{1}{|S_0^p(\mathbf{x})|} \sum_{i \in S_0^p(\mathbf{x})} Y_i$$

ITE → LSE

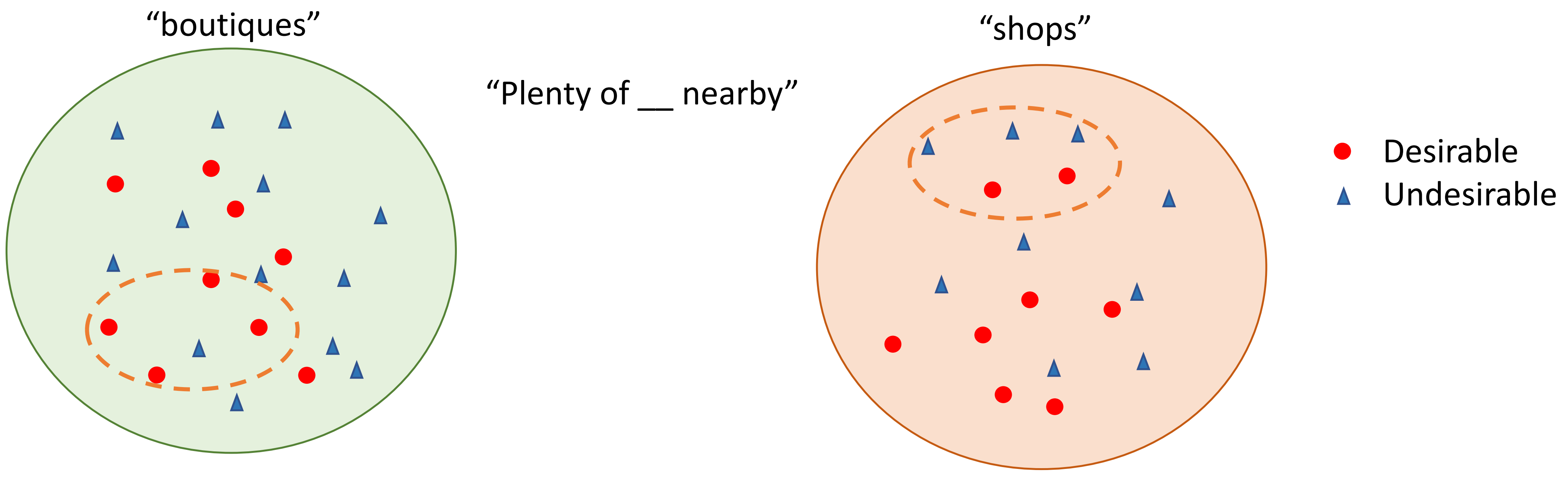
	Clinical Domain	Language Domain	Example
X	covariate vector for an individual	words in a sentence, omitting the word to be substituted	*"Plenty of __ nearby"*
T	drug treatment indicator	word substitution indicator	$T = 0$: *"Plenty of* **shops** *nearby"* $T = 1$: *"Plenty of* **boutiques** *nearby"*
Y	health outcome	human perception	Human perception of the desirability of a rental listing containing the sentence *"Plenty of boutiques nearby"*

Methods

- Quasi-experiment with observational data $(\boldsymbol{w_i}, \boldsymbol{w_j}, \boldsymbol{s})$
    1. KNN --> *K-Nearest Neighbor matching*
    2. VT-RF --> *Virtual Twins Random Forest*
    3. CF-RF --> *Counterfactual Random Forest*
    4. CSF --> *Causal forest*

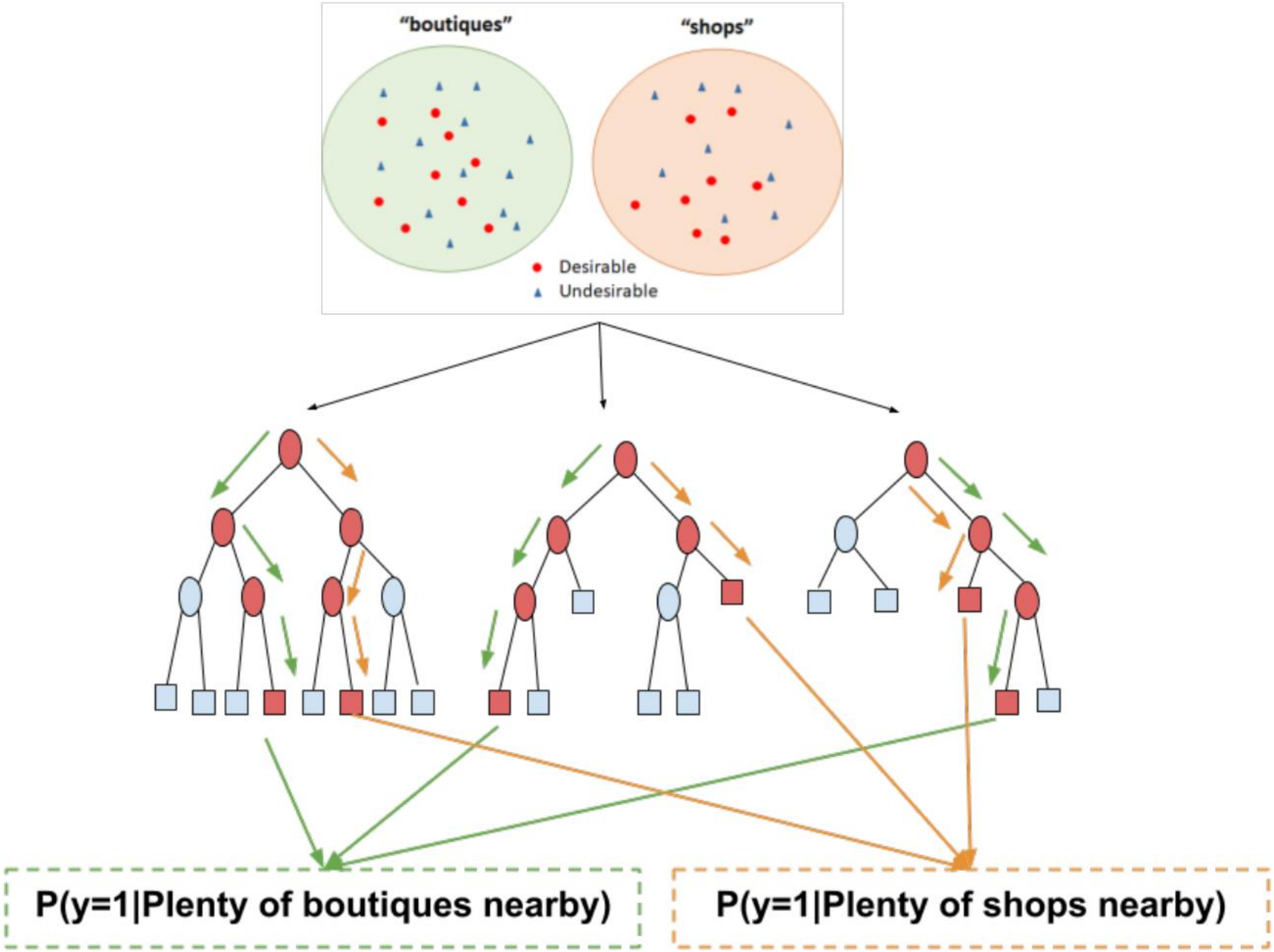
- Classification $(\boldsymbol{w_i}, \boldsymbol{w_j}, \boldsymbol{s}, \tau)$
    1. Causal perception classifier (RCT)

KNN: *K-Nearest Neighbor matching*



$$\hat{\tau}_{KNN}(\mathbf{x}) = \Big(\frac{1}{K}\sum_{i \in S_1(\mathbf{x},K)} Y_i\Big) - \Big(\frac{1}{K}\sum_{i \in S_0(\mathbf{x},K)} Y_i\Big)$$

VT-RF: *Virtual Twins Random Forest*

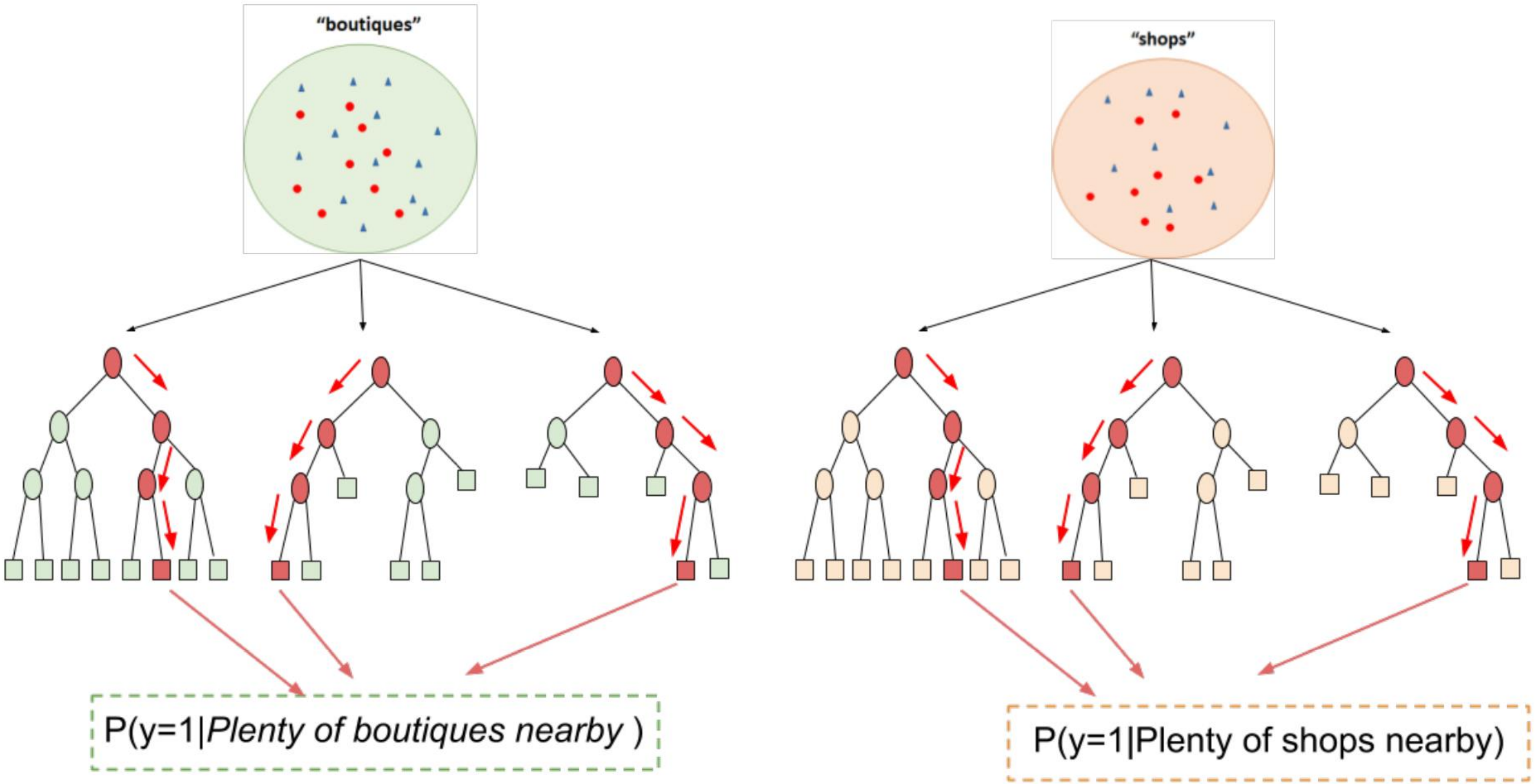


Virtual Twin:

- "Plenty of *shops* nearby"
- "Plenty of *boutiques* nearby"

$$\hat{\tau}_{VT}(\mathbf{x}) = \hat{Y}(\mathbf{x}, 1) - \hat{Y}(\mathbf{x}, 0)$$

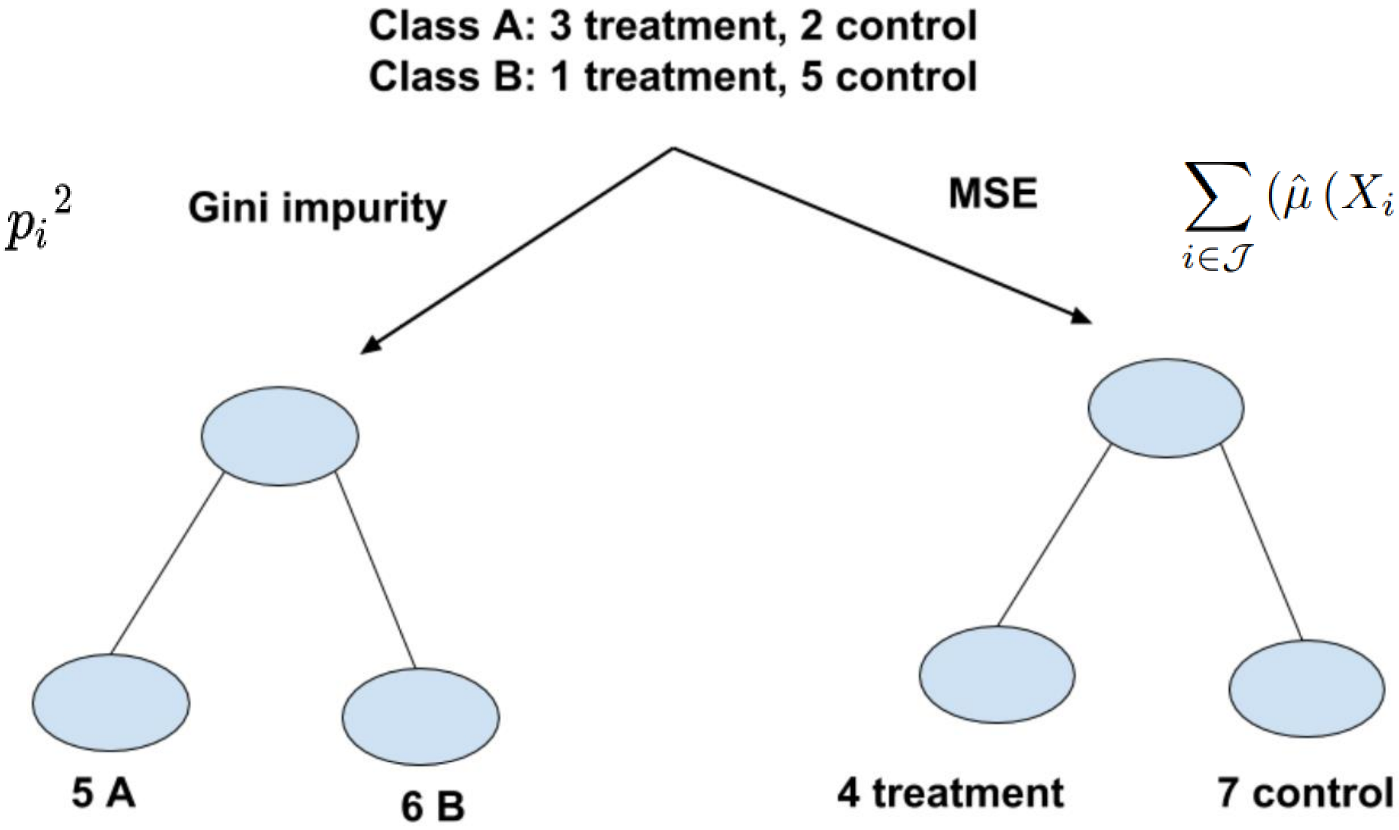
CF-RF: *Counterfactual Random Forest*



$$\hat{\tau}_{CF}(\mathbf{x}) = \hat{Y}_1(\mathbf{x}, 1) - \hat{Y}_0(\mathbf{x}, 0)$$

CSF: *Causal Forest*

$$1 - \sum_{i=1}^{J} {p_i}^2$$



$$\sum_{i \in \mathcal{J}} \left(\hat{\mu}\left(X_i\right) - Y_i\right)^2 = \sum_{i \in \mathcal{J}} Y_i^2 - \sum_{i \in \mathcal{J}} \hat{\mu}\left(X_i\right)^2$$

$$\hat{\tau}_{CSF}(\mathbf{x}) = \frac{1}{|L_1(\mathbf{x})|} \sum_{i \in L_1(\mathbf{x})} Y_i - \frac{1}{|L_0(\mathbf{x})|} \sum_{i \in L_0(\mathbf{x})} Y_i$$

Causal Perception Classifier

$$\begin{pmatrix}(w_{11}, w_{12}, s_1) \\ (w_{21}, w_{22}, s_2) \\ \ldots\ldots \\ (w_{n1}, w_{n2}, s_n)\end{pmatrix} \begin{pmatrix}\tau_1 \\ \tau_2 \\ \cdots \\ \tau_n\end{pmatrix} \xrightarrow{\text{Training}} \text{Classifier} \xrightarrow{\text{Predicting}} \begin{pmatrix}(w'_{11}, w'_{12}, s'_1) \\ (w'_{21}, w'_{22}, s'_2) \\ \ldots\ldots \\ (w'_{m1}, w'_{m2}, s'_m)\end{pmatrix}$$

- Generalizable Features:
  - Context probability
  - Control word probability
  - Treatment word probability

Dataset

Data source	Word pairs	Female/ undesirable	Male / desirable
Twitter (Gender)	1,876	583,982 female sentences	441,562 male sentences
Yelp (Gender)	1,648	582,792 female sentences	492,893 male sentences
Airbnb (Desirability)	1,678	49,866 sentences of undesirable neighborhoods	224,603 sentences of desirable neighborhoods

Candidate Word Substitutions

- Moderately correlated
- Semantic substitutability:
  - Paraphrase Database (PPDB 2.0)
- Syntactic substitutability:
  - Part-of-speech tag
- Substitutability for a specific sentence:
  - N-grams

$$(w_i, w_j, s)$$

Increase desirability	**Increase male perception**
store $\rightarrow$ boutique	gay $\rightarrow$ homo
famous $\rightarrow$ grand	yummy $\rightarrow$ tasty
famous $\rightarrow$ renowned	happiness $\rightarrow$ joy
rapidly $\rightarrow$ quickly	fabulous $\rightarrow$ impressive
nice $\rightarrow$ gorgeous	bed $\rightarrow$ crib
amazing $\rightarrow$ incredible	amazing $\rightarrow$ impressive
events $\rightarrow$ festivals	boyfriends $\rightarrow$ buddies
cheap $\rightarrow$ inexpensive	purse $\rightarrow$ wallet
various $\rightarrow$ several	precious $\rightarrow$ valuable
yummy $\rightarrow$ delicious	sweetheart $\rightarrow$ girlfriend

Table 1: Samples of substitution words with high LSE

Human-derived LSE estimates (AMT)

	Airbnb	Twitter / Yelp
Q&A	Rate the desirability of a short-term apartment rental based on a single sentence.	Rate how likely you think this tweet / Yelp review sentence is written by male or female.
5	Very desirable	Very likely male
4	Somewhat desirable	Somewhat likely male
3	Neither desirable nor undesirable	Neutral, neither male nor female
2	Somewhat undesirable	Somewhat likely female
1	Very undesirable	Very likely female

Table 5: Amazon Mechanical Turk annotation guidelines

- *"There are plenty of <u>shops</u> nearby"* → *"There are plenty of <u>boutiques</u> nearby"*

Comparisons

	Yelp	**Twitter**	**Airbnb**
Agreements-pearson	0.557	0.576	0.513
KNN	0.474	0.291	0.076
VT-RF	0.747	0.333	0.049
CF-RF	0.680	0.279	0.109
CSF	0.645	**0.338**	0.096
Causal perception classifier	**0.783**	0.21	**0.139**

Table 2: Inter-annotator agreement and Pearson correlation between algorithmically estimated LSE and AMT judgment

Comparisons

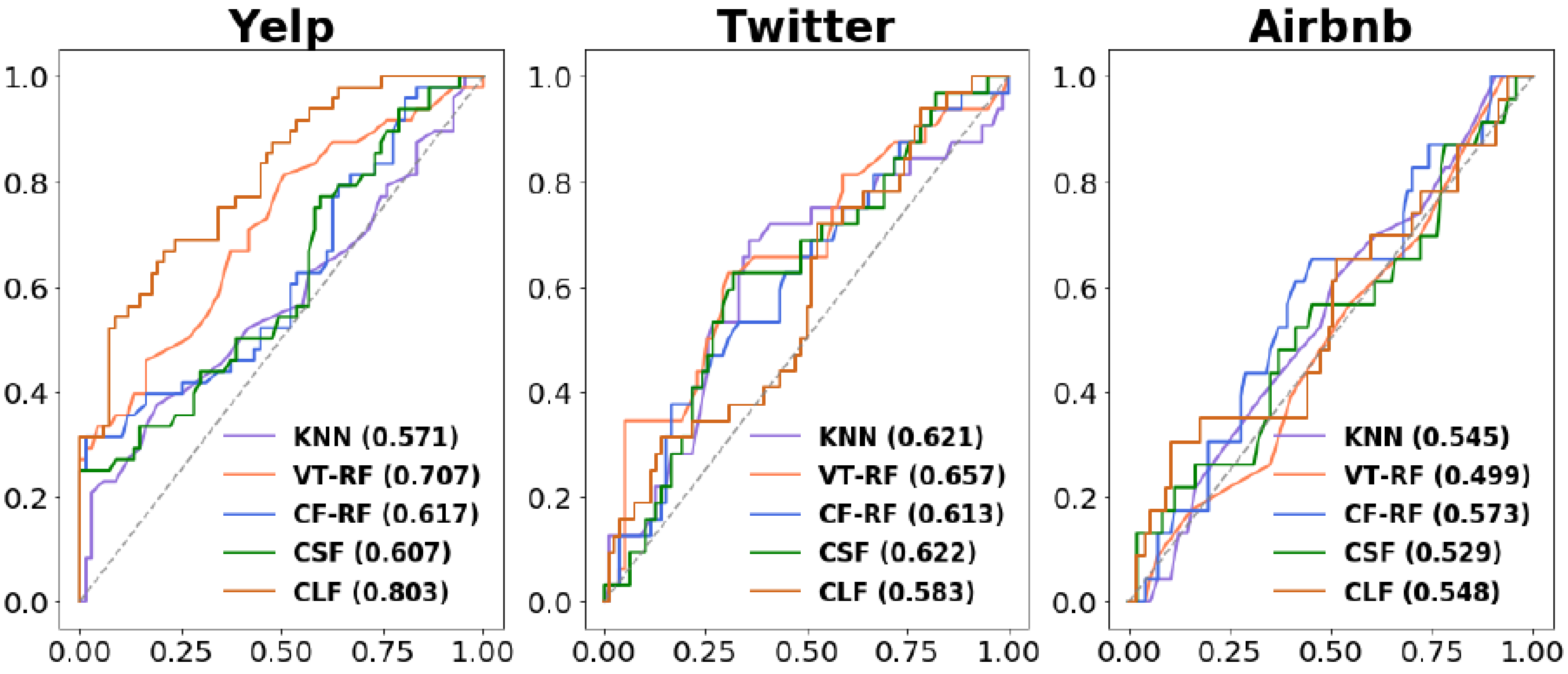


Figure 1: ROC curve for classifying sentences according to AMT perception with estimated LSE as confidence score

Causal perception classifier

	Yelp	Twitter	Airbnb
context pr	-0.348	-0.829	-0.528
control word pr	-0.141	-0.514	-0.367
treatment word pr	0.189	0.401	0.344

Table 3: Logistic regression coefficients for the features of the causal perception classifier

Conclusion example

- Monday nights are a night of bonding for me and my *boyfriend*
- Monday nights are a night of bonding for me and my *buddy*

- If you ask me to hang out with you and your *boyfriend*, I will ... decline.

Limitation and Future Work

- Crime rate as desirability
- Single word substitution --> multiple word substitutions
- Perception based on one sentence --> Perception based on documents

Thank You!