



# Interpretability

Advanced Machine Learning for NLP Jordan Boyd-Graber
NEED FOR INTERPRETABILITY

# **Trust Part of ML Pipeline**

Learn model

Trust model

Deploy model

Trust AI system



Make better decisions



Improve model



### ML is Everywhere

- Authorizing credit
- Sentencing guidelines
- Prioritizing services
- College acceptance
- Suggesting medical treatment

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### ML is Everywhere

- Authorizing credit
- Sentencing guidelines
- Prioritizing services
- College acceptance
- · Suggesting medical treatment
- How do we know it isn't being incompetent/evil?









Female voices pose a bigger challenge for voice-activated technology than men's voices

### To predict and serve?

Kristian Lum, William Isaac

First published: 7 October 2016 Full publication histor



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Users by Race

Facebook Lets Advertisers Exclude

Abstract

Uber seems to offer better service in areas arch for a person's name, such as "Trevon Jones", may yield a with more white people. That raises some d ad for public records about Trevon that may be neutral, such as "Trough Jones? ...", or may be suggestive of an arrest record, such as ested?...". This writing investigates the delivery of these kinds of

> Washington Heights Southwest Washingt

tough questions.

POLICE



**Machine Bias** 

There's software used across the country to predict future criminals. And it's biased against blacks.

1 Natalie Smith, Mark Josephs, Jan-

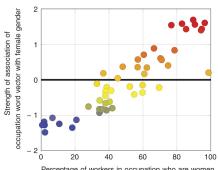
Dupont Circle Logan Circle

### Keep it Simple (Stupid)

- Clear preference for interpretability
- Even at the cost of performance: decision trees still popular
- But what about all of the great machine learning we've talked about?

### We've already seen problems

- Gender/racial bias
- Generalization failures
- Malicious Input



Percentage of workers in occupation who are women

#### We've already seen problems

- Gender/racial bias
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# Can we just remove problematic variables?

- Not obvious a priori
- Can find correlated features
- More of a problem in deep learning

# **Subject for Today**

- Intrinsic evaluation: topic models
- Intrinsic evaluation: embeddings
- Extrinsic evaluation: supervised ML
- Extrinsic evaluation: visualizations for supervised ML