

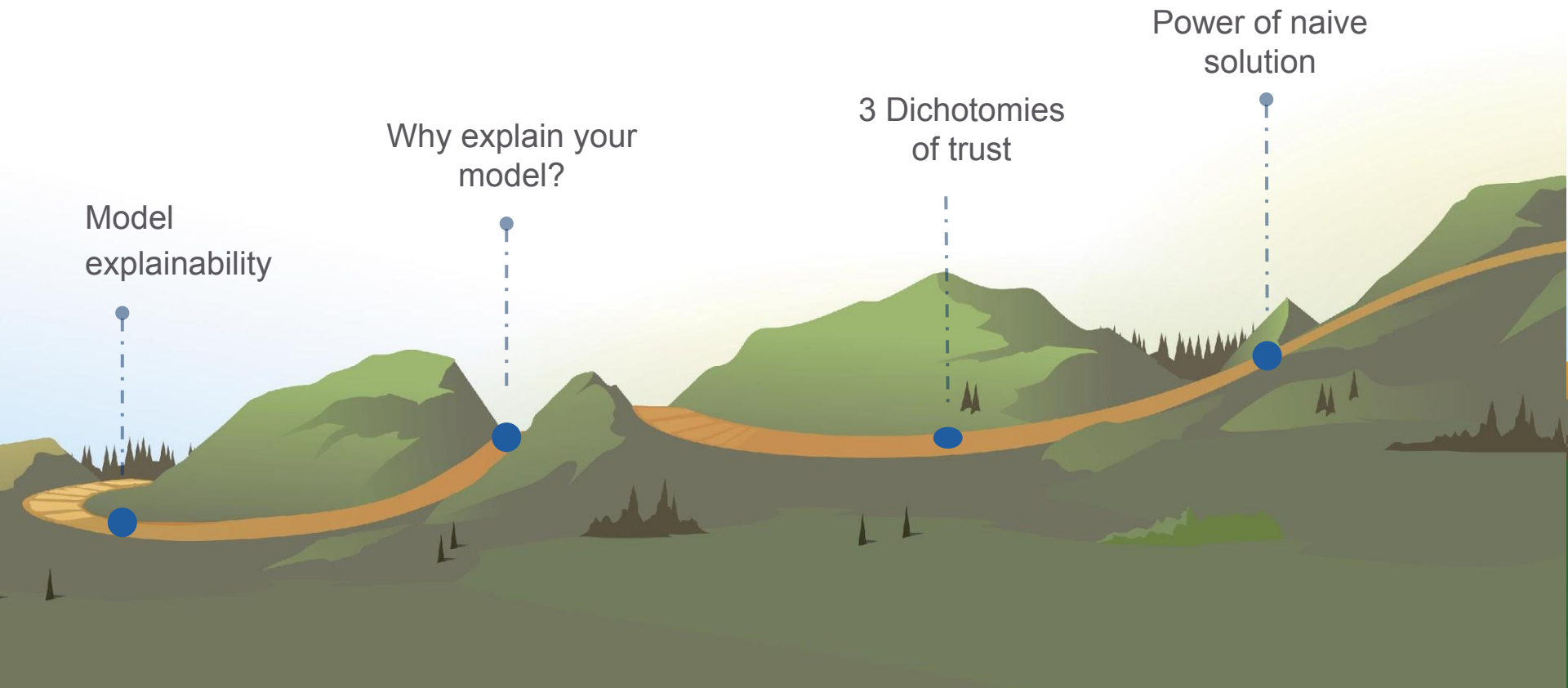
# Trustworthiness of Machine Learning Applications

Mayukh Bhaowal

Director of Product Management, Salesforce Einstein



# Roadmap for this talk



# The Question



“

Why did the machine learning model make the decision that it did?



# Translation #1



“

How do I fix this model?

— **Data Scientist**





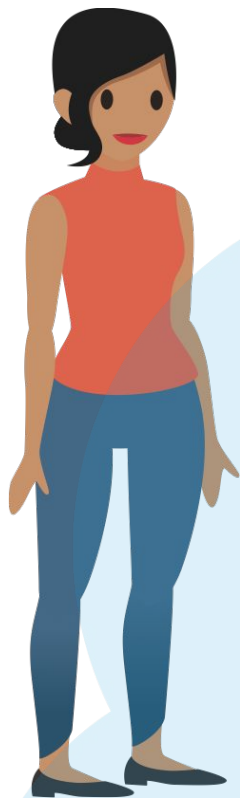
## Translation #2

“

Do we have our bases covered, in case of a regulatory audit?

— Legal Counsel





## Translation #3

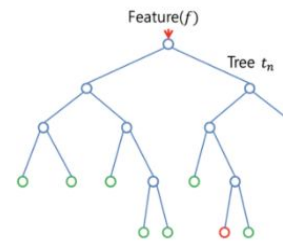
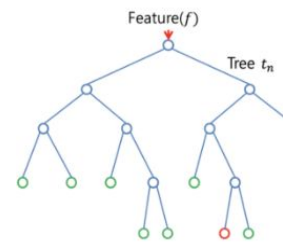
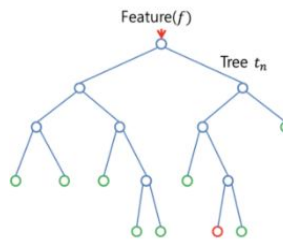
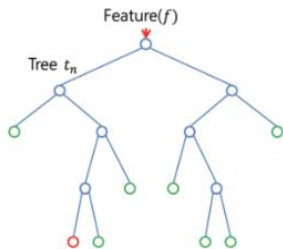
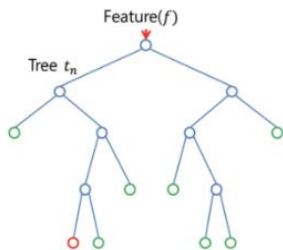
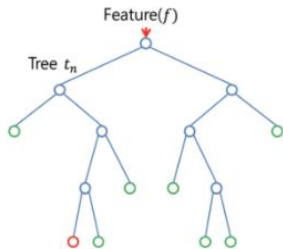
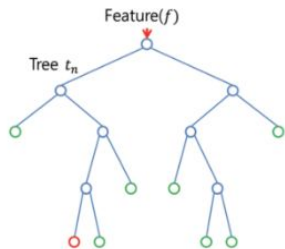
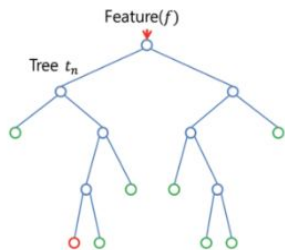
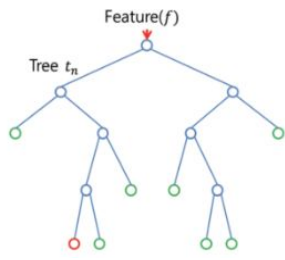
“

Does Einstein know what I know? How do I use this prediction?

— Non Technical End User



Input



BLACK BOX

$$P_1(c|f)$$

$$P_k(c|f)$$

$$P_n(c|f)$$

$\Sigma$

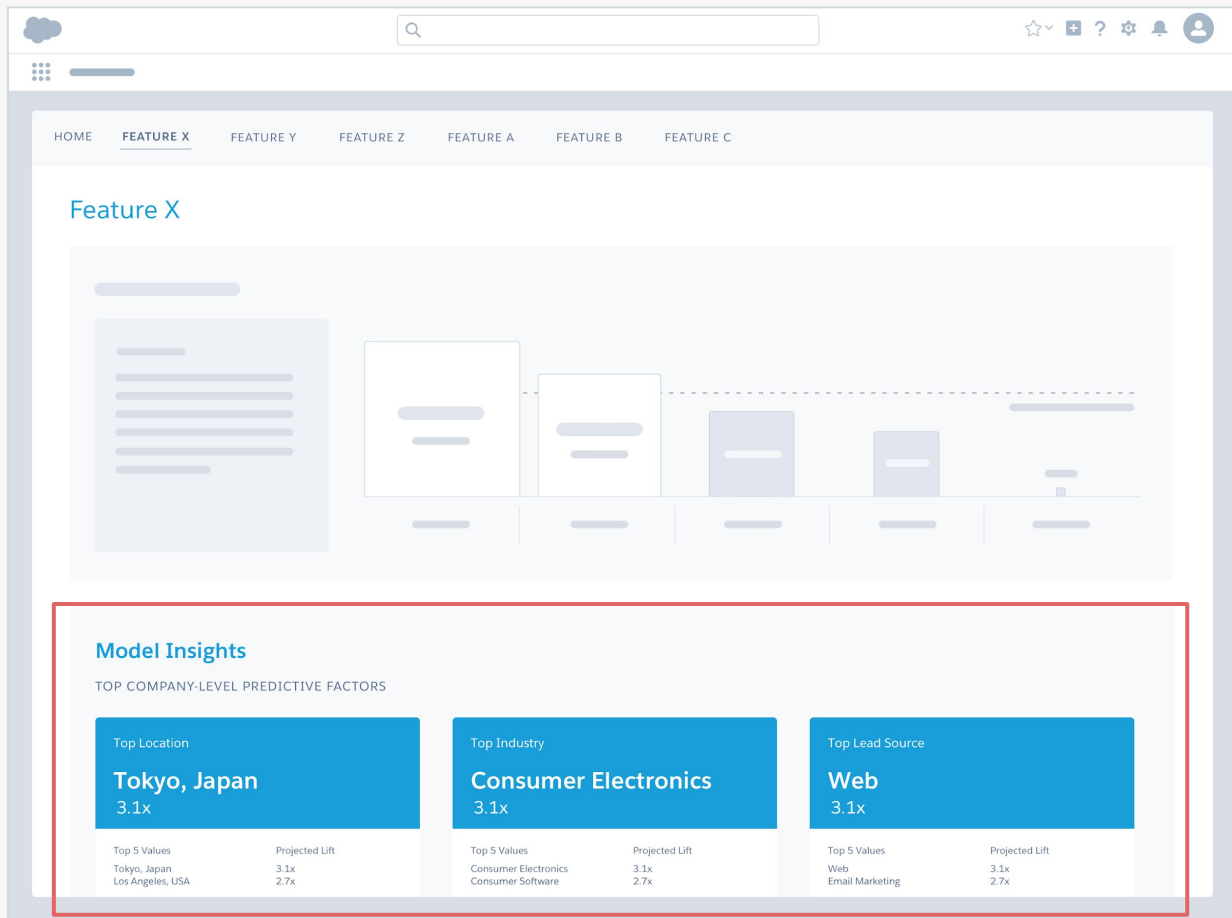
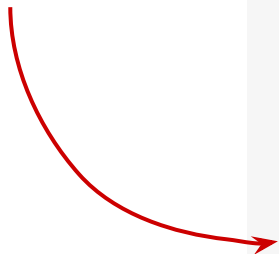
$$P(c|f) = \sum_1^n P_n(c|f)$$

Output

*"How do I know I can trust it?"*

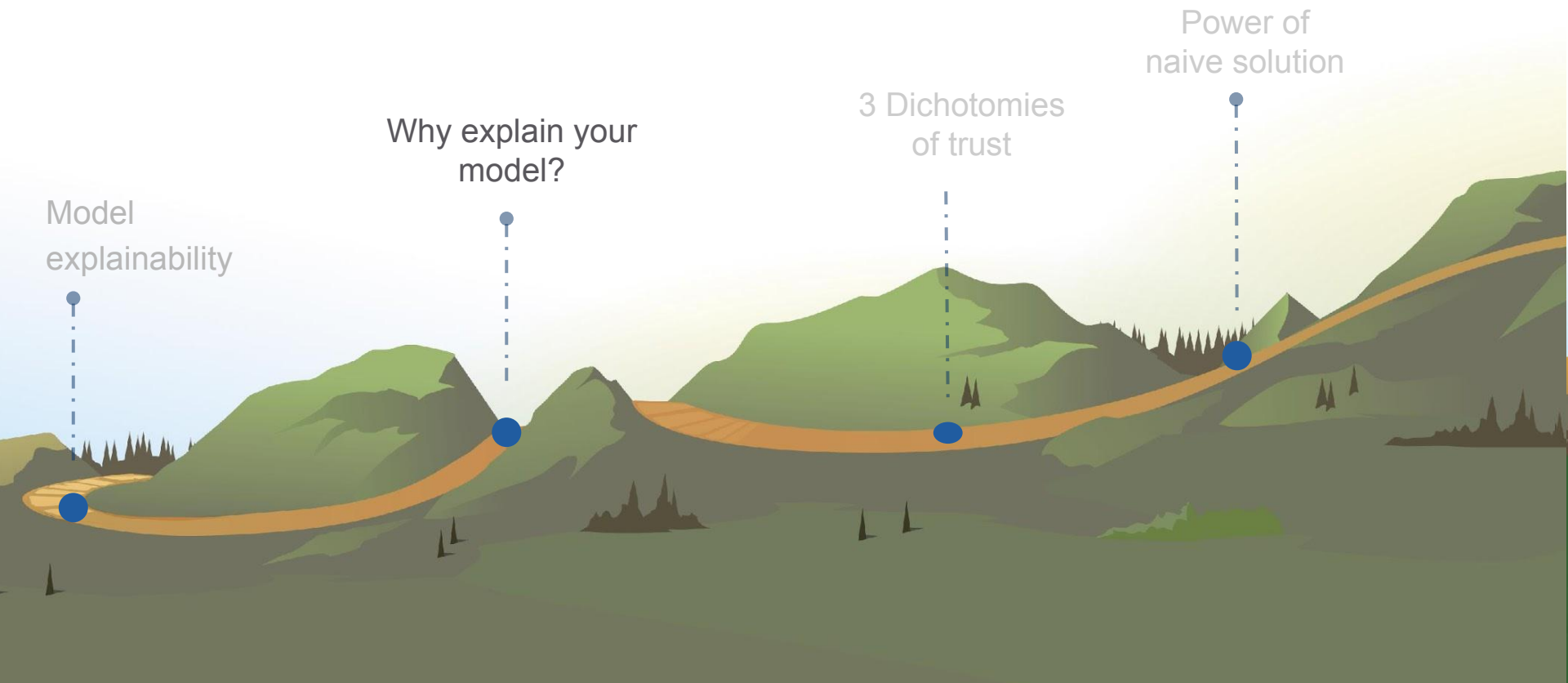
Idea Concept:

## Model Insights Report

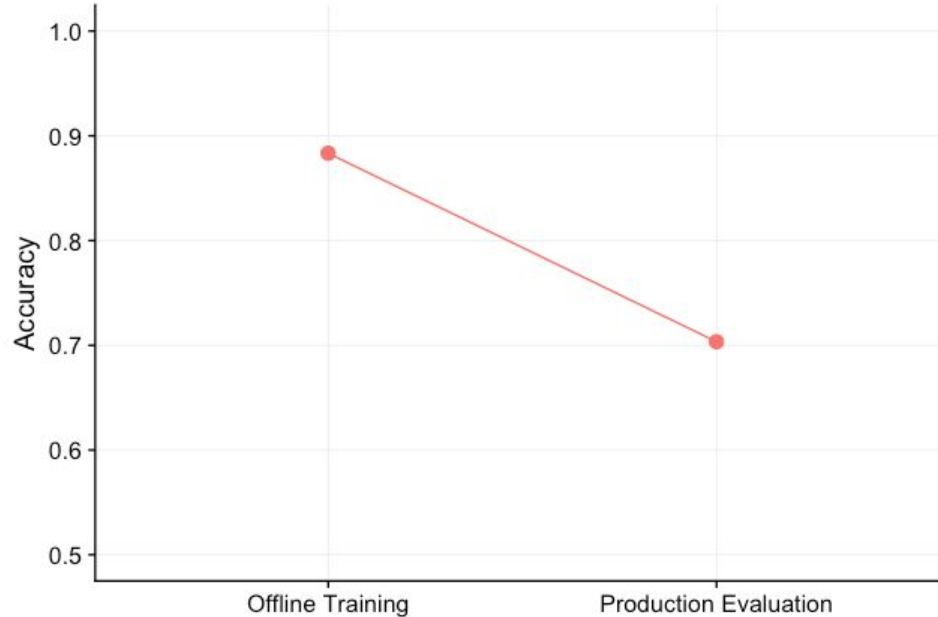




# Roadmap for this talk



# Debuggability



Top contributing features for predicting purchase:

1. Customer Interest Group
2. Thank you email
3. Customer Location

# Bias



TurkishChineseSpanishDetect language ▾

↔

EnglishChinese (Simplified)Spanish ▾

Translate

o bir asker  
o bir öğretmen  
O bir doktor  
o bir hemşire  
  
o bir yazar  
o bir kopek  
o bir dadı  
o bir kedi  
  
o bir rektör  
o bir başkan  
o bir girişimci  
o bir Şarkıcı  
o bir Öğrenci  
o bir Tercüman  
  
o çalışan  
o tembel  
  
o bir ressam  
o bir kuaför  
o bir garson  
O bir mühendis  
o bir mimar  
o bir Sanatçı

×

he is a soldier  
She's a teacher  
He is a doctor  
she is a nurse  
  
he is a writer  
he is a dog  
she is a nanny  
it is a cat  
  
he is a rector  
he is a president  
he is an entrepreneur  
she is a singer  
he is a student  
he is a translator  
  
he is hard working  
she is lazy  
  
he is a painter  
he is a hairdresser  
he is a waiter  
He is an engineer  
he is an architect  
he is an Artist

# Legal



OP-ED CONTRIBUTOR

# When an Algorithm Helps Send You to Prison

By Ellora Thadaney Israni

Oct. 26, 2017

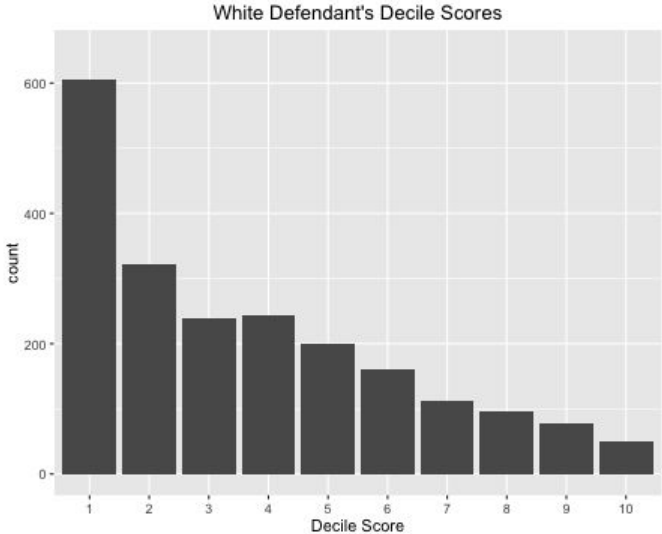
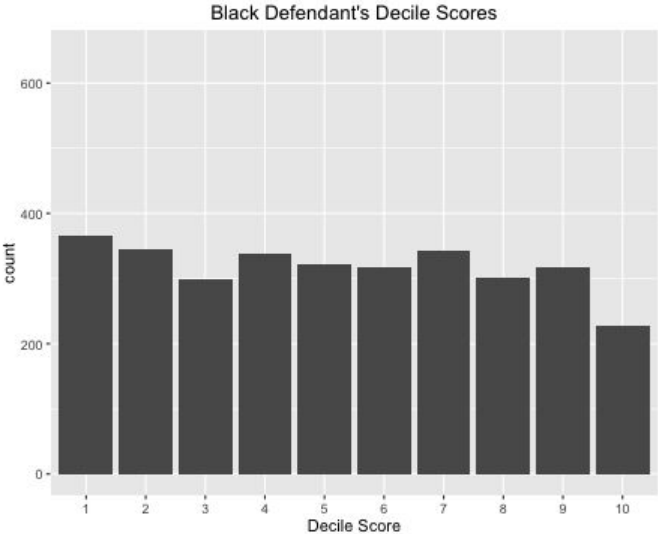
In 2013, police officers in Wisconsin arrested a man driving a car that had been used in a recent shooting. The man, Eric Loomis, pleaded guilty to attempting to flee an officer, and no contest to operating a vehicle without the owner's consent. Neither of his crimes mandates prison time.

At Mr. Loomis's sentencing, the judge cited, among other factors, Mr. Loomis's high risk of recidivism as predicted by a computer program called COMPAS, a risk assessment algorithm used by the state of Wisconsin. The judge denied probation and prescribed an 11-year sentence: six years in prison, plus five years of extended supervision.

No one knows exactly how COMPAS works; its manufacturer refuses to disclose the proprietary algorithm. We only know the final risk assessment score it spits out, which judges may consider at sentencing.

Mr. Loomis challenged the use of an algorithm as a violation of his due

# Black defendant has higher risk scores



# Actionable



The screenshot shows the Salesforce Einstein interface for a lead. A circular callout highlights the 'Lead Score' section, which displays a score of 92 and a list of 'TOP PREDICTIVE FACTORS'. The factors are:

- Phone Number is Valid
- Title is Director
- Downloaded White Paper
- Interest in Cloud Manager
- Incomplete Free Trial Form

A red arrow points from the 'Downloaded White Paper' factor to the 'Download Now' button in the Version B mockup.

Version A

Version A mockup shows a contact form with a 'Submit' button. The form includes a 'Choose' dropdown menu and a 'CONTACT US' button.

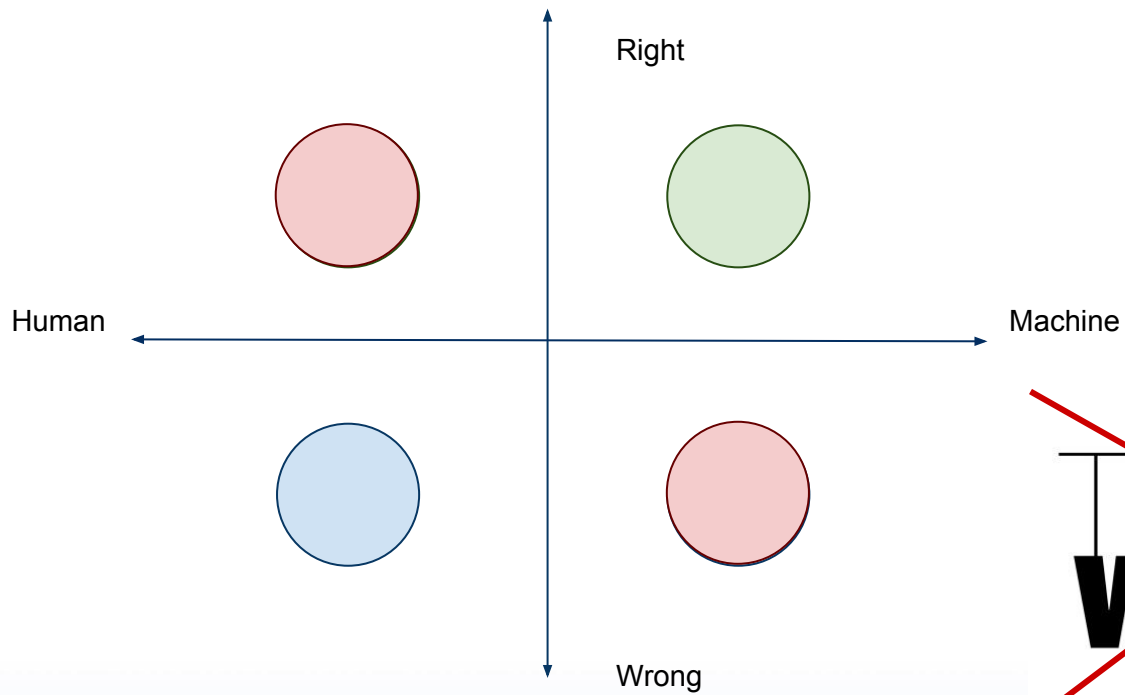
Version B

Version B mockup shows a contact form with a 'Choose' dropdown menu and a 'Download Now' button. The form includes a 'Choose' dropdown menu and a 'Download Now' button.

## Trust

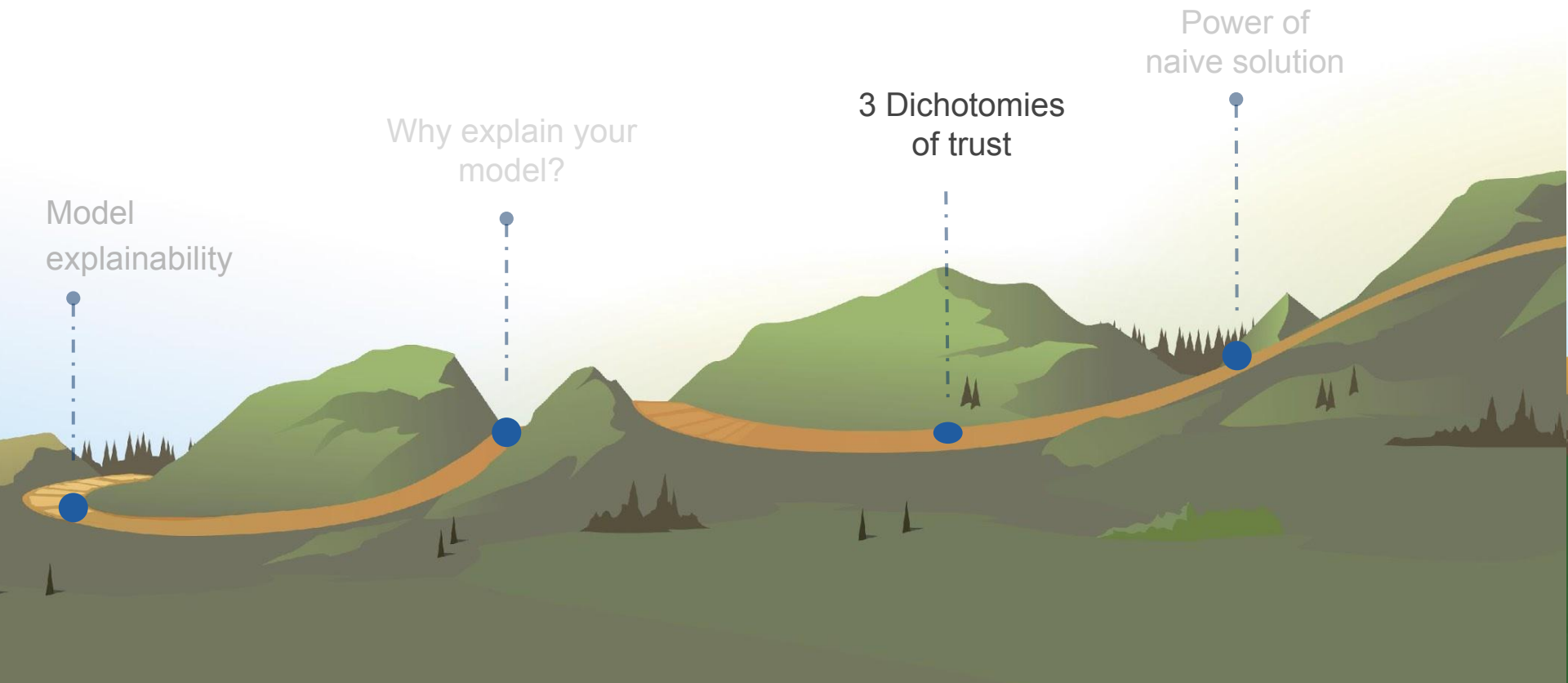
How can you trust a man that wears both a belt and suspenders? Man can't even trust his own pants.





~~TRUST  
WORTHY~~

# Roadmap for this talk



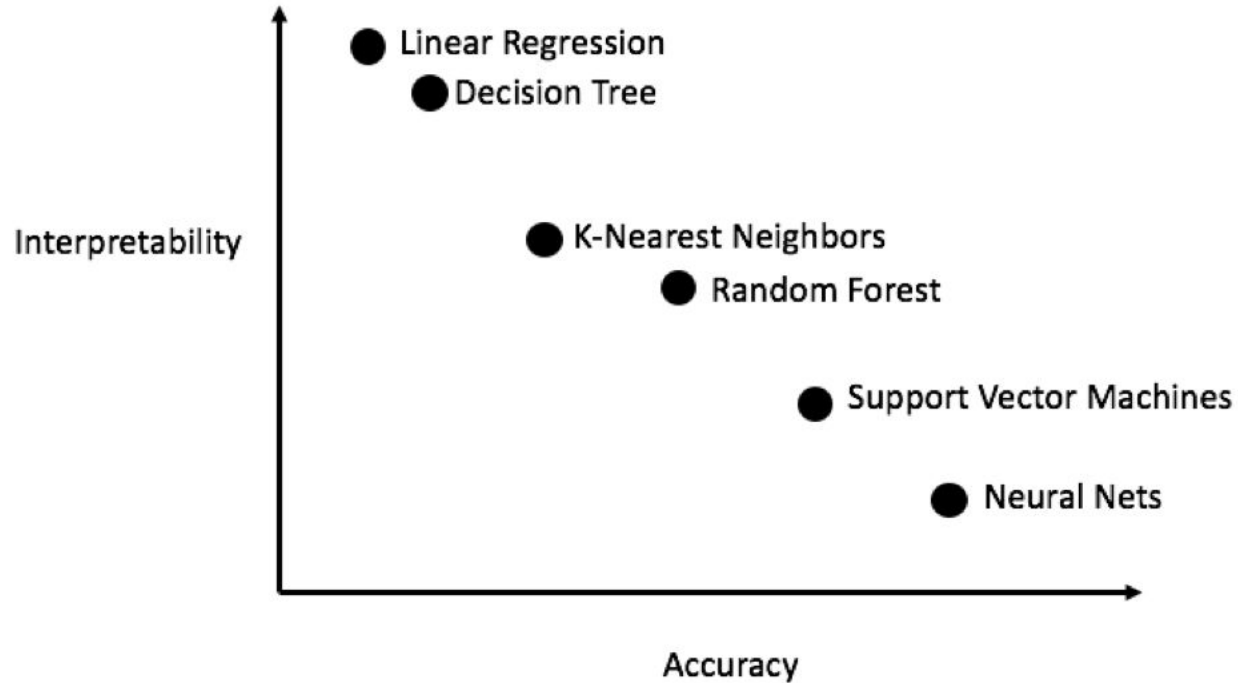
# The 3 Dichotomies of Trust

Explainability Accuracy

Global Explanations Local Explanations

Model Aware Model Agnostic

# 1. Explainability vs Accuracy



# Example of Text Feature Engineering

Representing the word **overfitting** using various feature representations:

**Morphological** = [(prefix, **over-**), (root, **fit**), (suffix=imperfect tense, **-ing**)]

**Unigrams** = ['o', 'v', 'e', 'r', 'f', 'i', 't', 't', 'i', 'n', 'g']

**Bigrams** = ['ov', 've', 'er', 'rf', 'fi', 'it', 'tt', 'ti', 'in', 'ng']

**Trigrams** = ['ove', 'ver', 'erf', 'rfi', 'fit', 'itt', 'tti', 'tin', 'ing']

**One-hot** = [0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]

**Word vector** = [-0.26, 0.34, 0.48, -0.06, 0.16, 0.11, 0.13, -0.15, 0.47, -0.49, 0.07, -0.39, -0.13, -0.15, 0.06, 0.09]

## 2. Global vs Local Explanations



# Predict House Price

| Size (feet <sup>2</sup> )<br><u><math>x_1</math></u> | Number of<br>bedrooms<br><u><math>x_2</math></u> | Number of<br>floors<br><u><math>x_3</math></u> | Age of home<br>(years)<br><u><math>x_4</math></u> | Price (\$1000)<br><u><math>y</math></u> |
|--|--|--|---|---|
| 2104   | 5  | 1  | 45  | 460                                     |
| 1416   | 3  | 2  | 40  | 232                                     |
| 1534   | 3  | 2  | 30  | 315                                     |
| 852  | 2  | 1  | 36  | 178                                     |
| ...  | ...  | ...  | ...   | ...                                     |

$$h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \theta_4 x_4$$

e.g.  $\underline{h_{\theta}(x)} = \underline{80} + \underline{0.1}x_1 + \underline{0.01}x_2 + \underline{3}x_3 - \underline{2}x_4$

↑
↑
↑
age

# Predict House Price

| Size (feet <sup>2</sup> )<br>$x_1$ | Number of bedrooms<br>$x_2$ | Number of floors<br>$x_3$ | Age of home (years)<br>$x_4$ | Price (\$1000)<br>$y$ |
|------------------------------------|-----------------------------|---------------------------|------------------------------|-----------------------|
| 2104                               | 5                           | 1                         | 45                           | 460                   |
| 1416                               | 3                           | 2                         | 40                           | 232                   |
| 1534                               | 3                           | 2                         | 30                           | 315                   |
| 852                                | 2                           | 1                         | 36                           | 178                   |
| ...                                | ...                         | ...                       | ...                          | ...                   |

$$h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \theta_4 x_4$$

e.g.  $\underline{h_{\theta}(x)} = \underline{80} + \underline{0.1}x_1 + \underline{0.01}x_2 + \underline{3}x_3 - \underline{2}x_4$

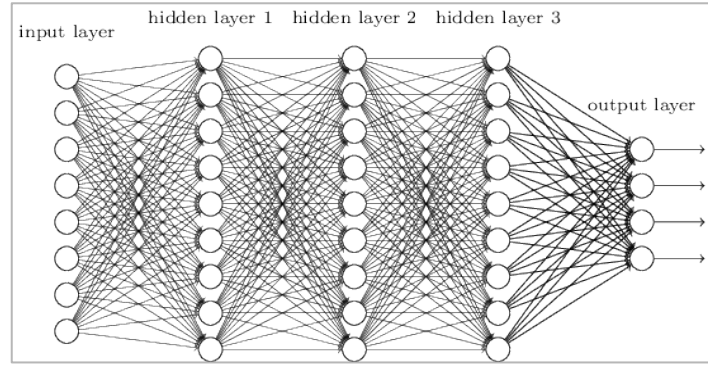
852
2
1
36



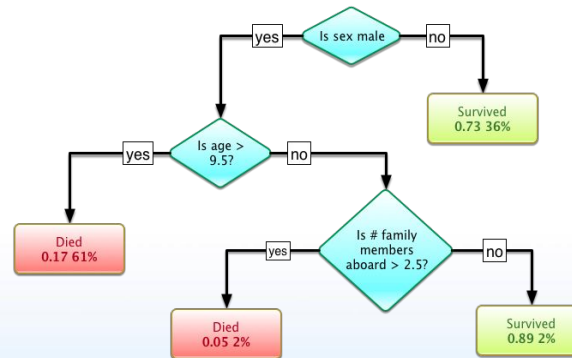
### 3. Model Aware vs Model Agnostic



Input

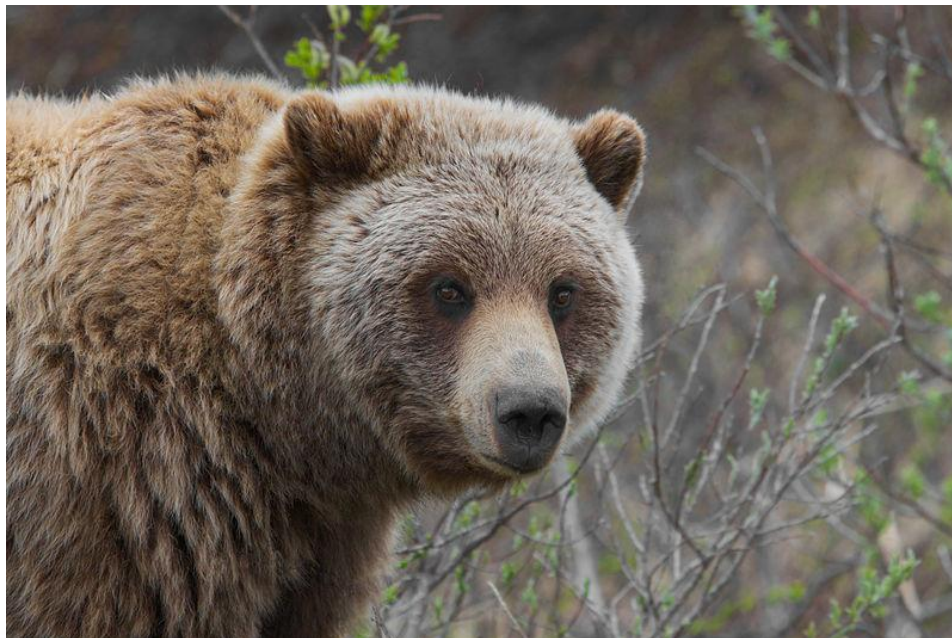


Prediction

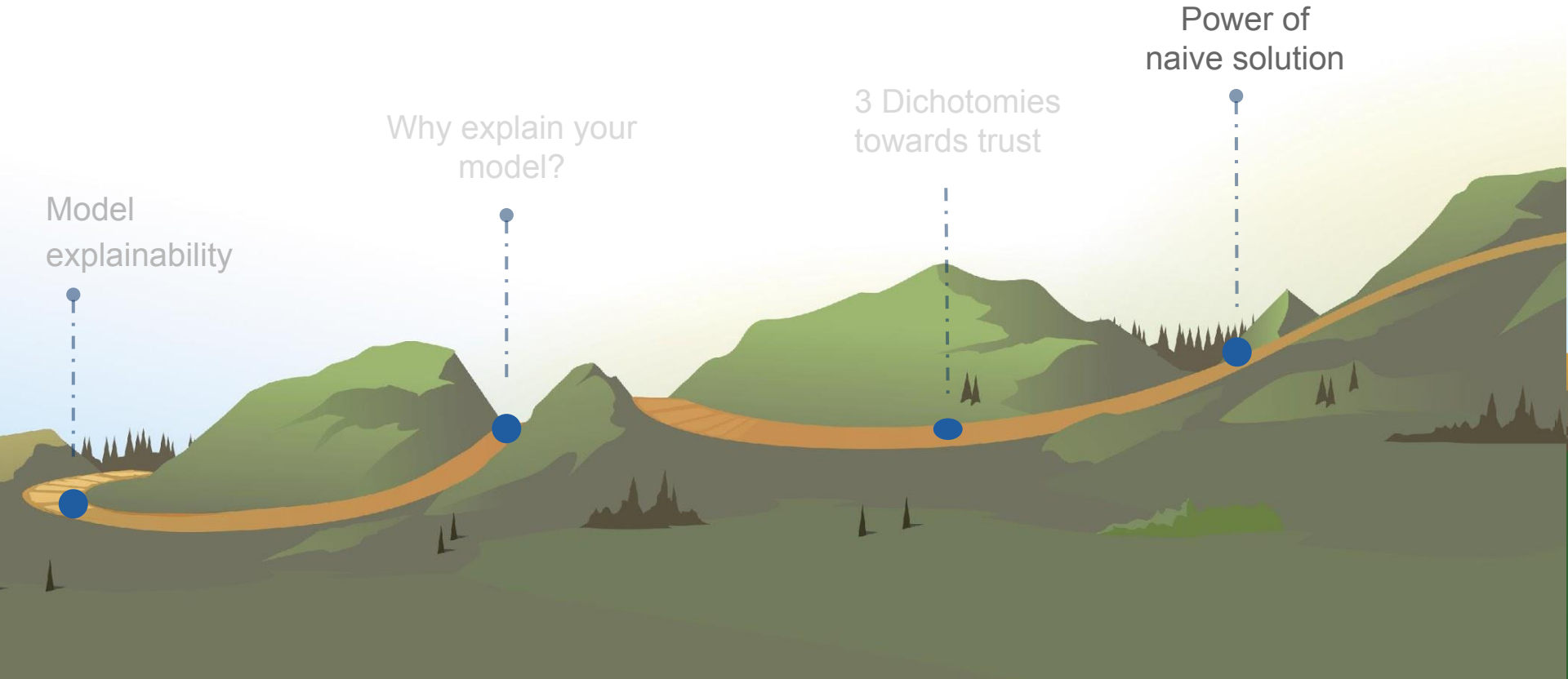


Explanation

# Model Agnostic Explanations



# Roadmap for this talk



# Meet 80% of Customer Needs with Naive Solution



The source of this lead is an inbound call and leads with such source generally have a high chance of converting

**Einstein**

92 Lead Score

TOP PREDICTIVE FACTORS

- Phone Number is Valid
- Title is Director
- Downloaded White Paper
- Interest in Cloud Manager
- Incomplete Free Trial For

**Customer Report**

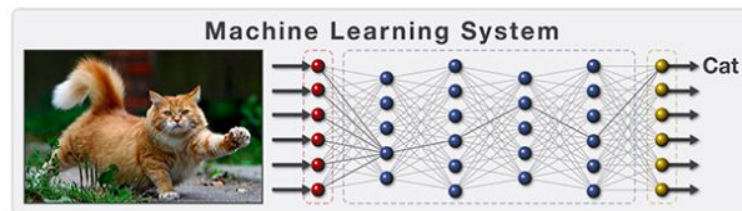
Customer 123  
Churn Probability: 24%

|                  |         |
|------------------|---------|
| Contract         | Monthly |
| Tenure           | 16      |
| Internet Service | DSL     |

**Suggested Action**  
Upgrade the customer to a yearly contract to reduce their churn probability by 12%.

Feature Importance (More likely to churn): Low High

Feature Importance (Less likely to churn): Low High



This is a cat:

- It has fur, whiskers, and claws.
- It has this feature:

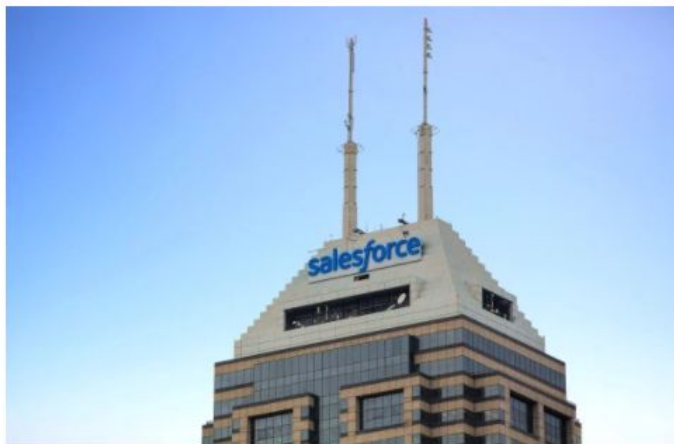




AI

## Salesforce open-sources TransmogrifAI, the machine learning library that powers Einstein

KYLE WIGGERS @KYLE\_L\_WIGGERS AUGUST 16, 2018 6:00 AM

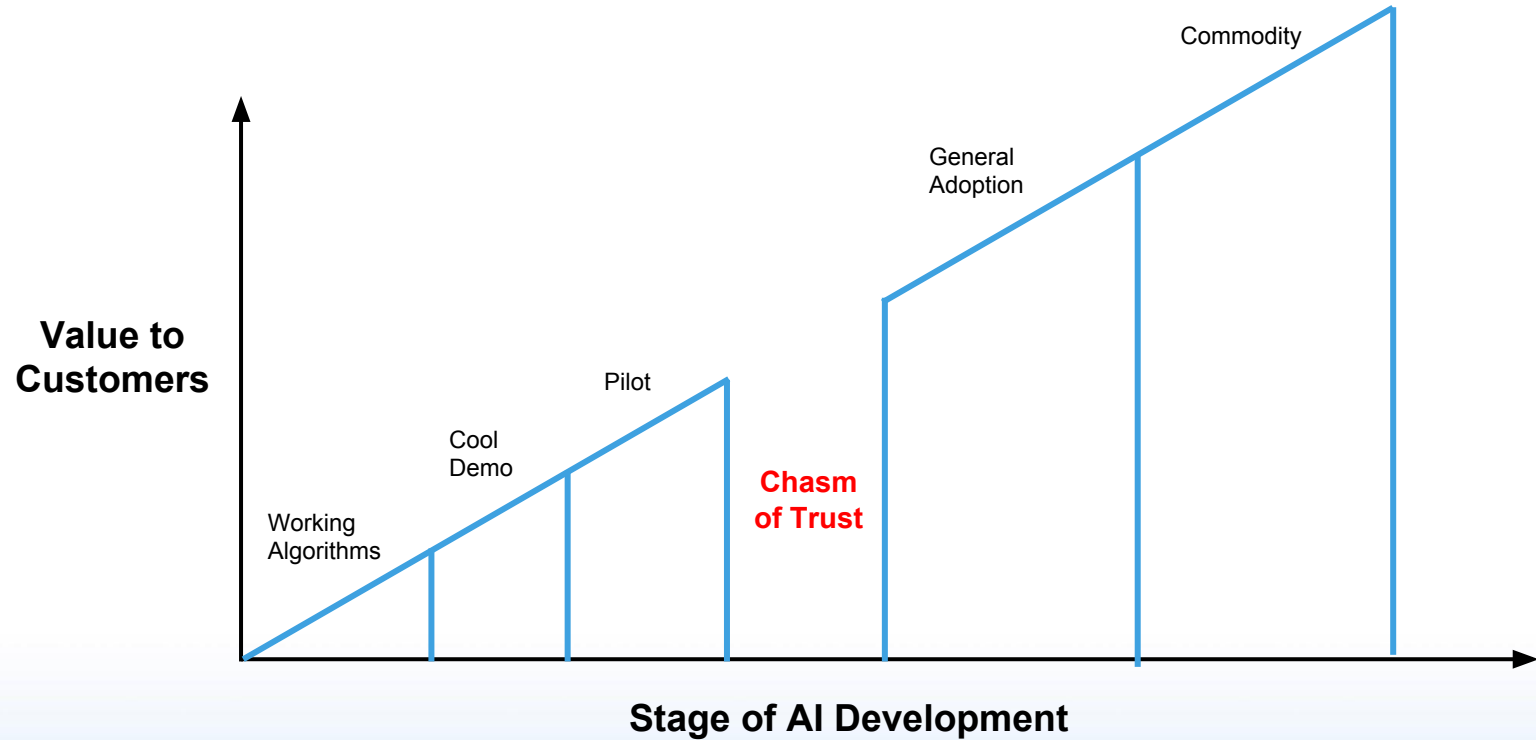


Above: Salesforce Tower in Indianapolis is the company's largest hub outside its global headquarters in San Francisco. It opened on May 20, 2016.

Image Credit: Salesforce

Machine learning models — artificial intelligence (AI) that identifies relationships among hundreds, thousands, or even millions of data points — are rarely easy to architect. Data scientists spend weeks and months not only preprocessing the data on which the models are to be trained, but extracting useful features (i.e., the data types) from that data, narrowing down algorithms, and ultimately building (or attempting to build) a system that performs well not just within the

# Lack of Trust is a Barrier to Adoption





# Thank You!

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Email: [mbhaawal@salesforce.com](mailto:mbhaawal@salesforce.com)

