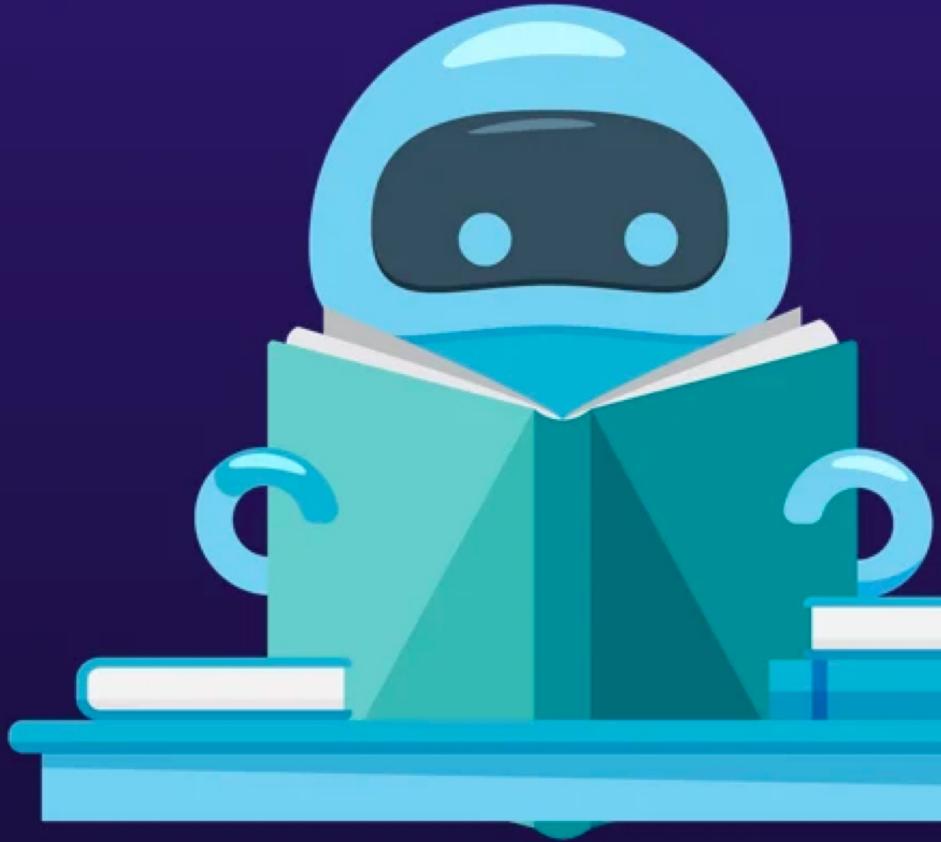


Gender equality and Machine Learning



Agenda

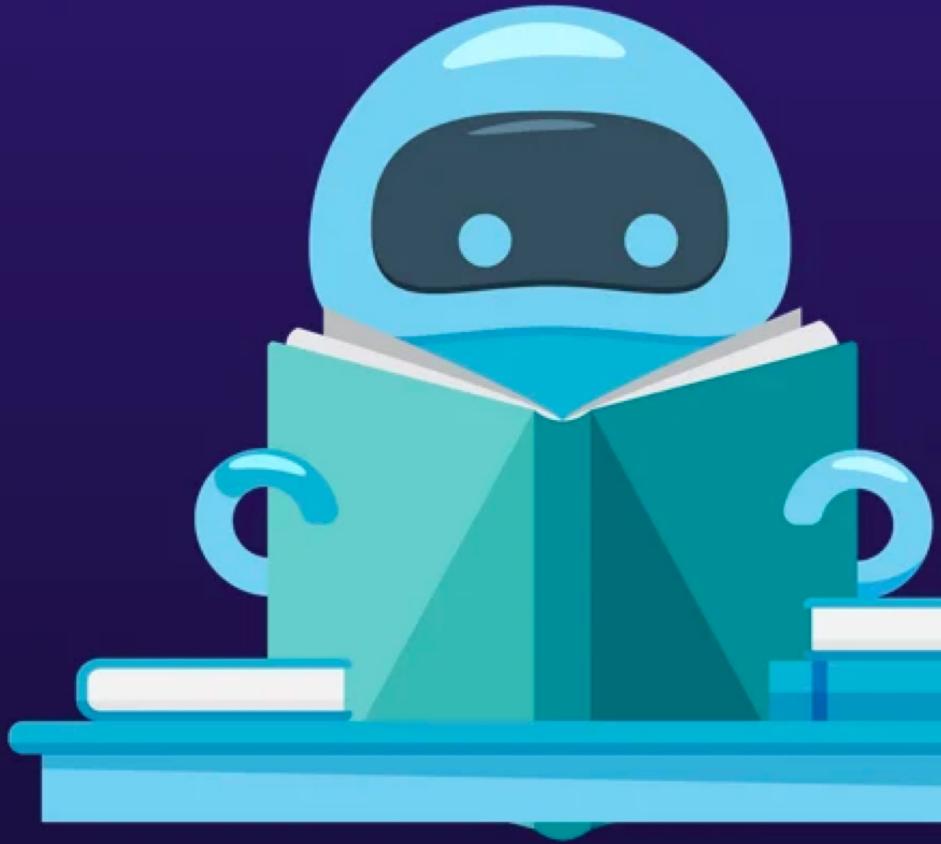
- ✓ What is (and is **NOT**) Machine Learning
- ✓ A context on Gender Equality
- ✓ Live Code! 🚀



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Agenda

- ✓ What is (and is **NOT**) Machine Learning
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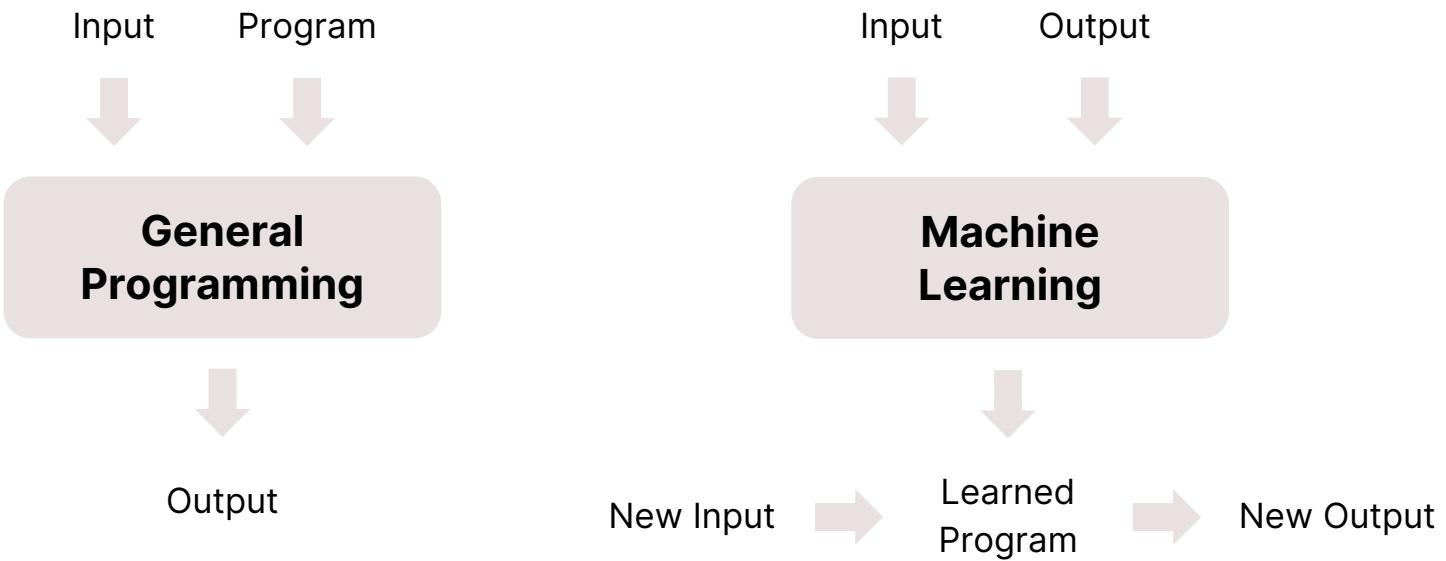


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“[a] field of study that gives computers the **ability to learn without being explicitly programmed”**

Arthur Samuel (1959)





How Machine Learning works ?



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Take basics Observations

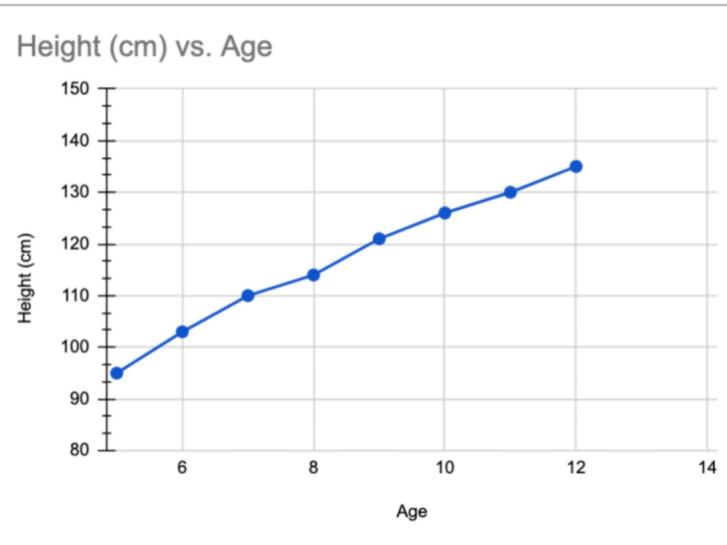
My Age / Height ratio ↪

Age	Height (cm)
5	95
6	103
7	110
8	114
9	121
10	126
11	130
12	135

Feature Target
Input Output

Infer a **Math function**

How tall was I at 13? 🧑



Extrapolate for new observations

Easy guess, isn't it ?



**What if there are 150 different features
and a million observations
for 2 million different people?**



**What if there are 150 different features
and a million observations
for 2 million different people?**

Every day.



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**What if there are different features
and a million observations
for 2 million different people?**

Every day.

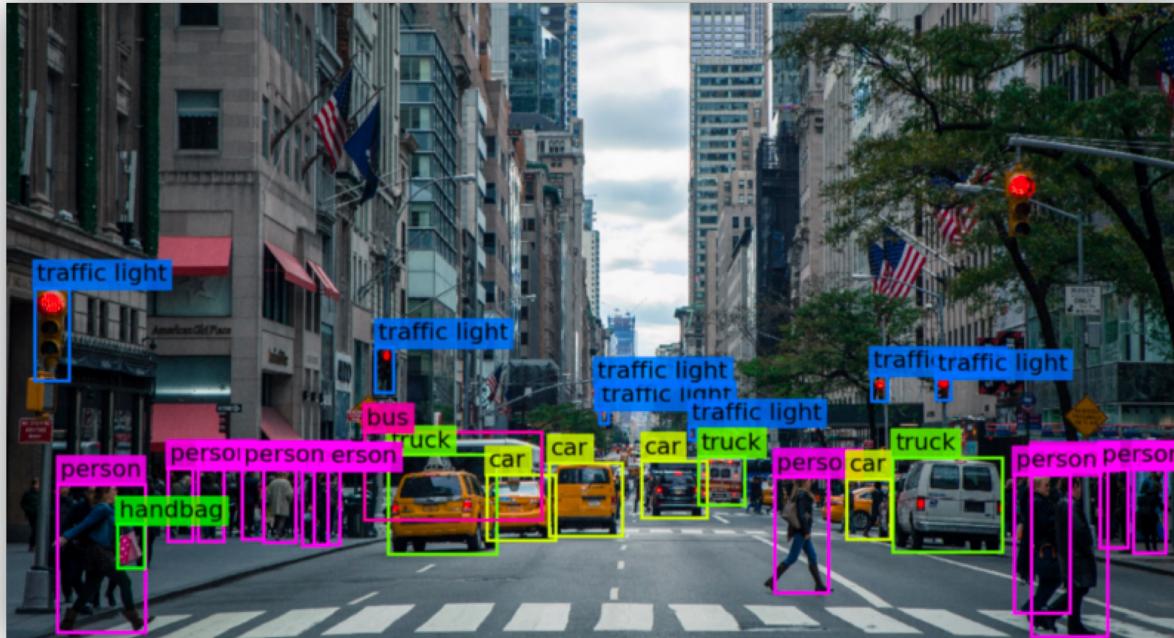
**Machine Learning is
already all *around us***



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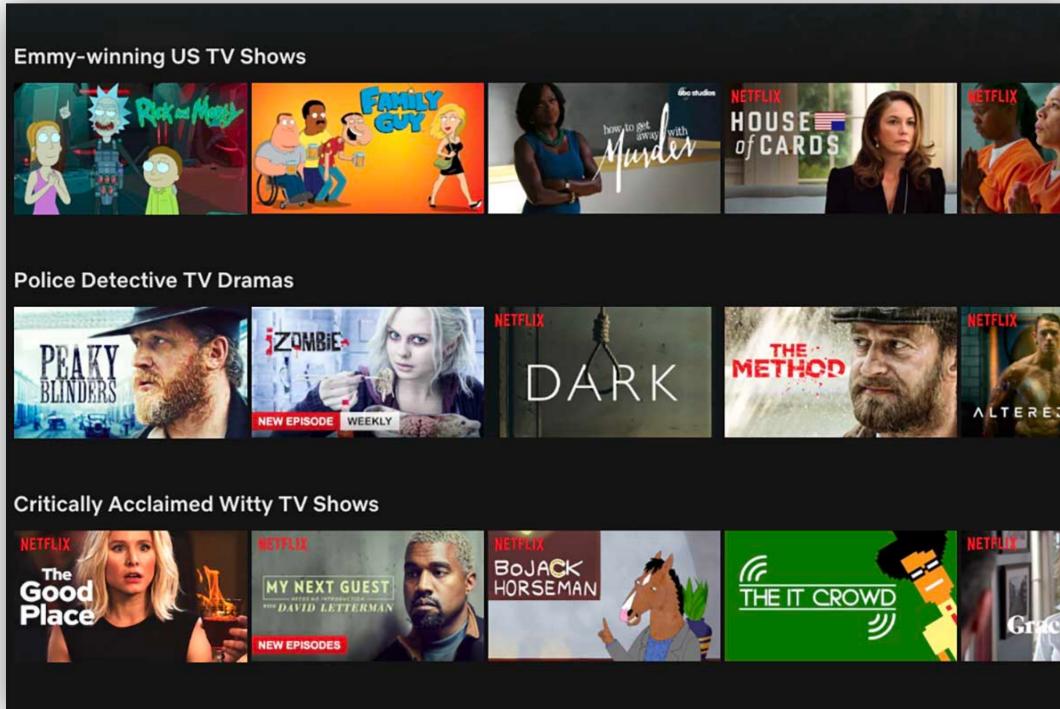
Computer Vision

Classifying and detecting visual data



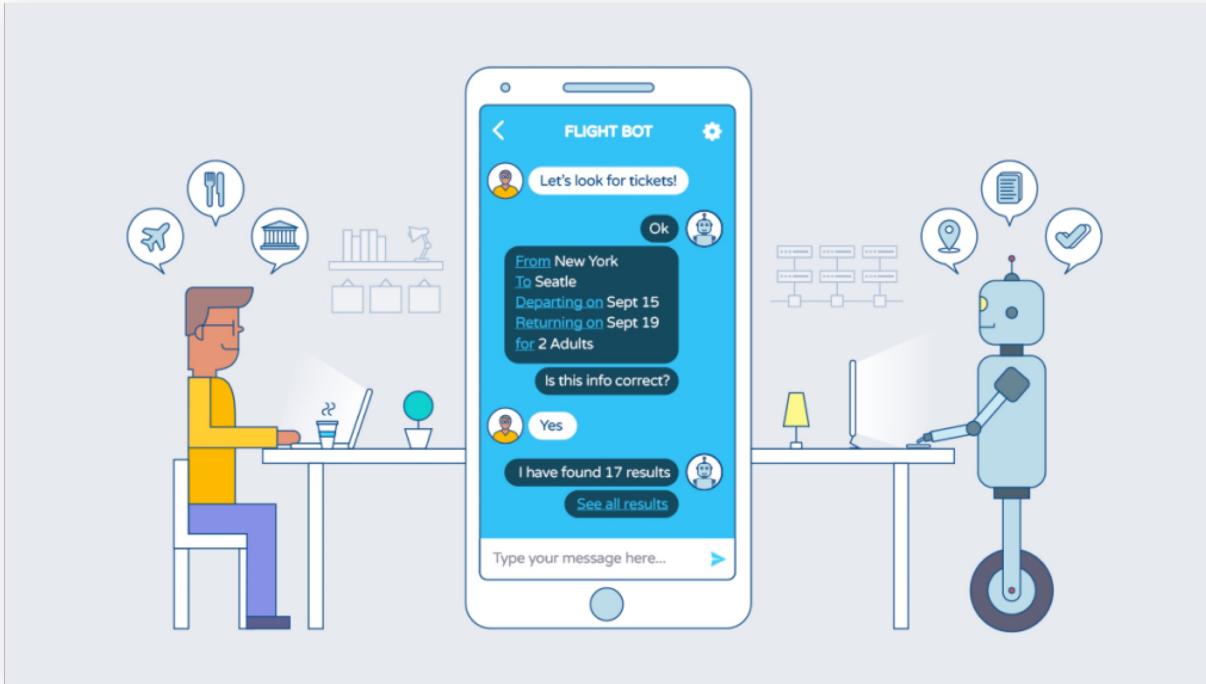
Recommendation Engine

Predicting your next action



Natural Language Processing

Finding meaning in text



Time Series

Can past change predict future change



Anomaly Detection

“Predicting patterns” in reverse

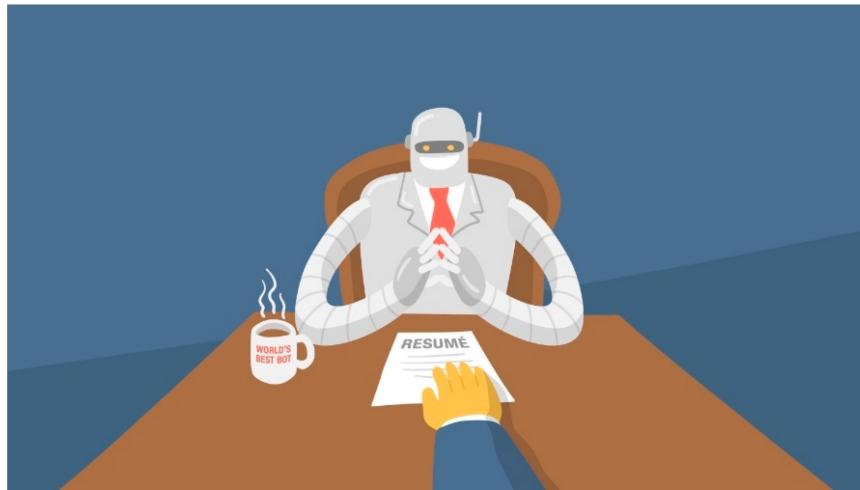


When Machine Learning becomes just **hype**



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Missing ground truth



Machine Learning for hiring the perfect candidate!

Things have **changed**

Let's take a drug dose analysis 💊

Day 1 - 10mg

Day 2 - 15mg

Day 3 - 20mg **Day 6 - ?**

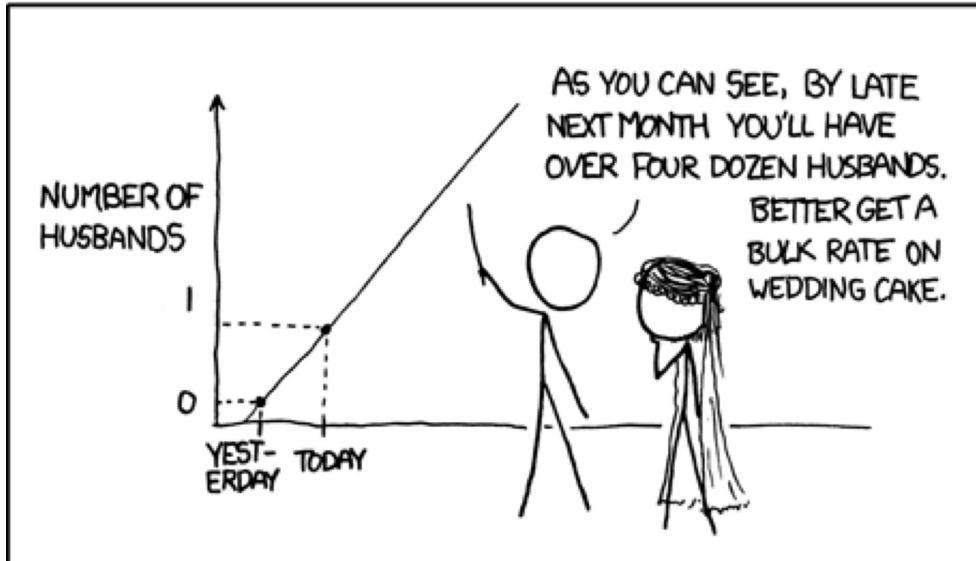
Day 4 - 25mg

Day 5 - 30mg



Things have **changed**

MY HOBBY: EXTRAPOLATING



Things have **really changed**

TECH \ CORONAVIRUS

The algorithms big companies use to manage their supply chains don't work during pandemics

The data the algorithms use isn't reliable

By Nicole Wetsman | April 27, 2020, 1:25pm EDT

Listen to this article



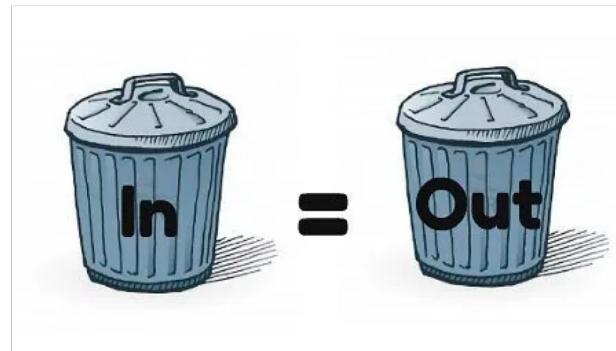
f t SHARE

AD

VERGE DEALS

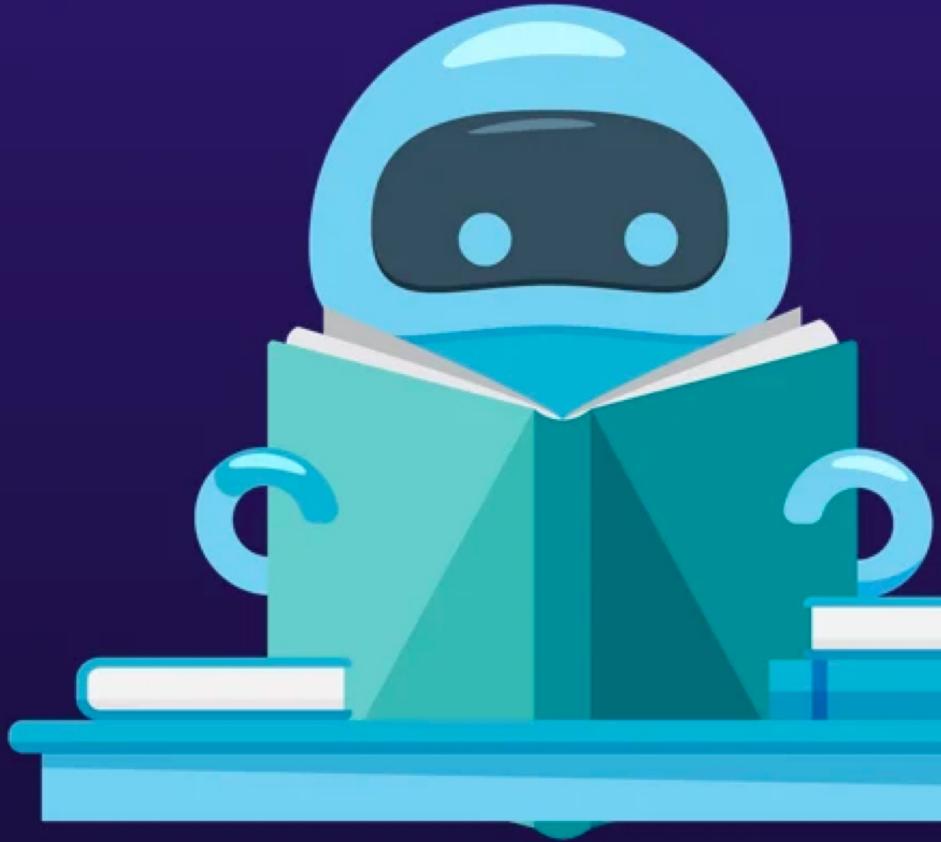
Most firms that think they want advanced AI/ML really just need linear regression on **cleaned-up data**

— Robin Hanson (@robinhanson) November 28, 2016



Agenda

- ✓ What is (and is **NOT**) Machine Learning
- ✓ **A context on Gender Equality**
- ✓ Live Code! 🚀



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What is Gender Equality?

Let's first do a quick research on the topic.

“Equal rights, responsibilities and opportunities of women and men and girls and boys.”

Source: European Institute for Gender Equality

“ Equality does not mean that women and men will become the same but that women’s and men’s rights, responsibilities and opportunities will not depend on whether they are born female or male. (...) ”

Source: European Institute for Gender Equality

Some **references** to look at



<https://www.coe.int/en/web/genderequality/themes>



<https://www.humanrightscareers.com/issues/causes-gender-inequality/>



<https://www.mckinsey.com/featured-insights/diversity-and-inclusion/ten-things-to-know-about-gender-equality>



<https://eige.europa.eu/news/covid-19-derails-gender-equality-gains>



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Data Science use cases

Some examples of how Data Science can have an impact on Gender Equality.



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Data Science use cases.

Only a few examples.

Make gender data visible.



[check this report](#)

Predict gender based violence.



[check this paper](#)

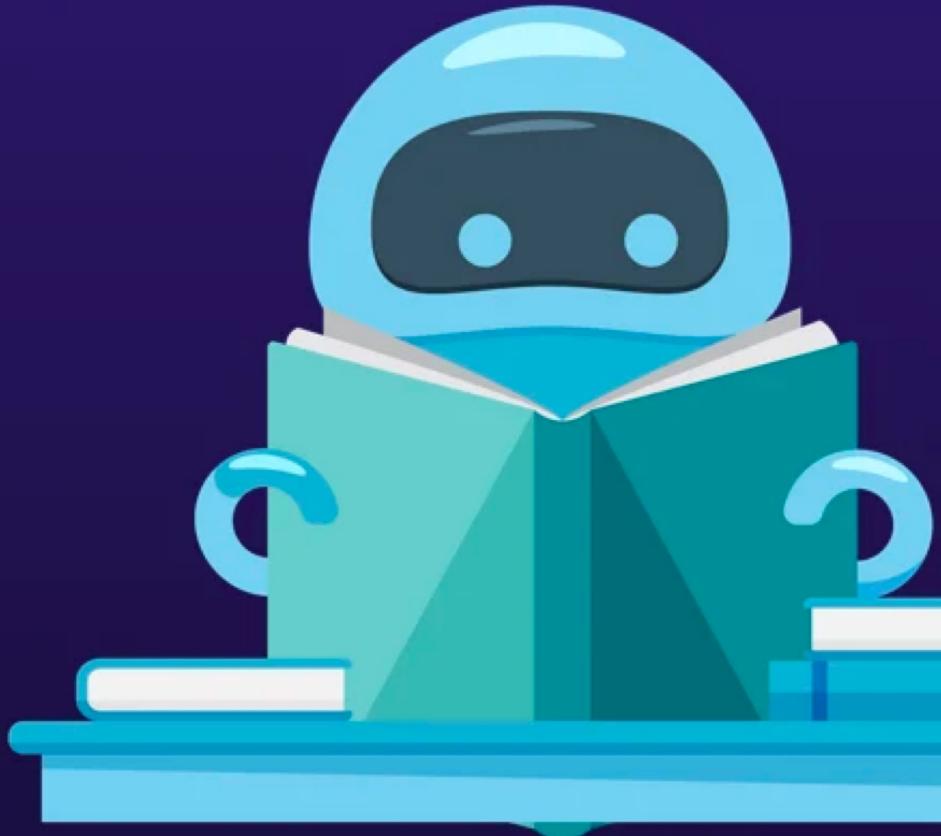
Know the causes for gender pay gap.



[check these articles](#)

Agenda

- ✓ What is (and is **NOT**) Machine Learning
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Ready to get **nerdy**?



RStudio Connect

https://colorado.rstudio.com/rsc/jupyter-notebook-visualization/jupyter-static-visualization.html

Python Visualization Libraries

```
In [1]: import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

Matplotlib

```
In [2]: np.random.seed(0)

mu = 200
sigma = 25
x = np.random.normal(mu, sigma, size=100)

fig, (ax0, ax1) = plt.subplots(ncols=2, figsize=(8, 4))

ax0.hist(x, 20, density=1, histtype='stepfilled', facecolor='g', alpha=0.75)
ax0.set_title('stepfilled')

# Create a histogram by providing the bin edges (unequally spaced).
bins = [100, 150, 180, 195, 205, 220, 250, 300]
ax1.hist(x, bins, density=1, histtype='bar', rwidth=0.8)
ax1.set_title('unequal bins')

fig.tight_layout()
plt.show()
```



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Before Machine Learning

We can do some **analysis**



What's the data

Understand what we have

- ✓ How many rows and columns?
- ✓ What are the columns we have?
- ✓ What are the averages?
- ✓ What are the minimums and maximums?

Methods to explore your data:

```
In [ ]: # to get the number of rows, columns  
salaries.shape
```

```
In [ ]: # to get the columns and their data types  
salaries.dtypes
```

```
In [ ]: # to get a readable summary of your data  
round(salaries.describe())
```



Visualize the data

Get an intuition of what it tells you

- ✓ How many of each category we have?
- ✓ Do any two columns relate to each other?
- ✓ Do some categories influence the output?
- ✓ First step of any Data Scientist!



Visualize the data

Get an intuition of what it tells you

- ✓ How many of each category we have?

```
In [ ]: # to count the distribution of values in a column  
sns.countplot(data=salaries, x='Column Name')
```

- ✓ Do any two columns relate to each other?

```
In [ ]: # to see the relation of one column to another  
sns.scatterplot(data=salaries, x='Input Column', y='Output Column')
```

- ✓ Do some categories influence the output?

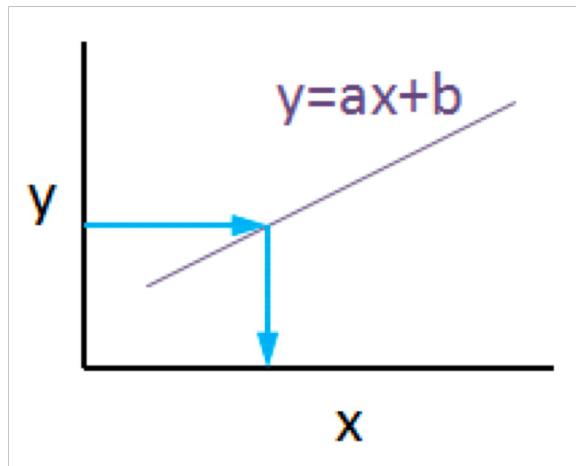
```
In [ ]: # to add a category to the visualization, we use `hue`  
sns.scatterplot(data=salaries, x='Input Column', y='Output Column', hue='Category Column')
```



Challenge 1:

Predicting salaries 

Linear Regression



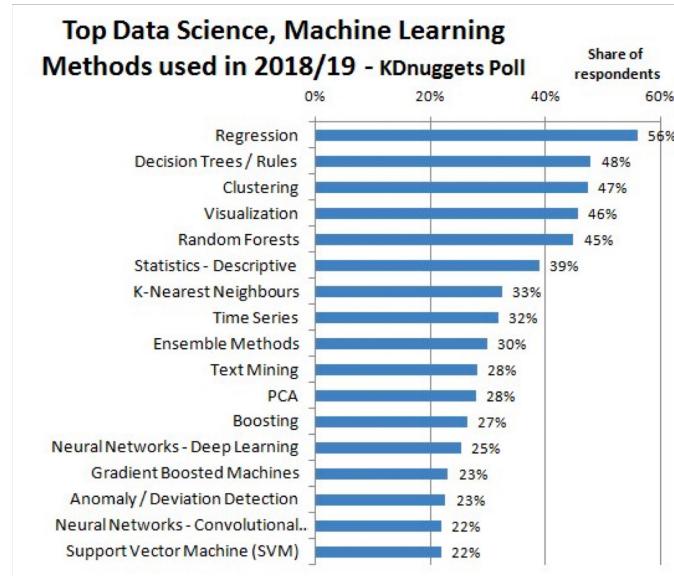
**Most firms that think they want advanced AI/ML really just
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Why Regression?



Visual demo on setosa.io! 

Road to Machine Learning

1. Select the **features** and **targets**
2. **Import** the model from Sklearn
3. **Train** the model
4. **Score** the model's performance
5. **Predict** with new data



Road to Machine Learning

1. Select the **features** and **targets**

Setting our features (inputs):

```
In [ ]: # we can select all needed columns...
features = salaries[["Gender", "Age", "Department_code", "Years_exp", "Tenure (months)"]]
```

```
In [ ]: # ...or we can simply drop the not needed!
features = salaries.drop(["Department", "Gross"], axis="columns")
```

Setting our target (output):

```
In [ ]: # we can simply select the column we need
target = salaries["Gross"]
```



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Road to Machine Learning

1. Select the features and targets
2. Import the model from Sklearn
3. Train the model
4. Score the model's performance
5. Predict with new data

Once we find the model we need, it's easy to import

```
In [ ]: # the syntax looks like this  
from sklearn.MODEL_TYPES import MODEL_YOU_NEED
```

```
In [ ]: # with Linear Regression we need this  
from sklearn.linear_model import LinearRegression
```

After importing, we need to **initialize** the model, like this:

```
In [ ]: model = LinearRegression()
```

Road to Machine Learning

1. Select the **features** and **targets**
2. Import the model from Sklearn
3. Train the model
4. Score the model's performance
5. Predict with new data

To train the model, we use the `.fit` method:

```
In [ ]: model.fit(features, target)
```

The `model` then finds the **best fitting** line between features and target

Road to Machine Learning

1. Select the features and targets
2. Import the model from Sklearn
3. Train the model
4. **Score** the model's performance
5. Predict with new data

To score the model, we use the `.score` method:

```
In [ ]: model.score(features, targets)
```

We need to give it some **test data** to do the scoring

Road to Machine Learning

1. Select the features and targets
2. Import the model from Sklearn
3. Train the model
4. Score the model's performance
5. Predict with new data

To predict -- you guessed it ;)

We use the `.predict` method:

```
In [ ]: model.predict(new_data)
```

`new_data` is the info we want our model to use to predict a new target (output).

In our case, it's a new `hire` !

Road to Machine Learning

1. Select the **features** and **targets**
2. Import the model from Sklearn
3. Train the model
4. Score the model's performance
5. Predict with new data
6. **Explaining** the model

The things that a Linear Regression model "learns" are **coefficients** and **intercept**.

The **coefficients** show how each feature influences the target:

```
In [ ]: model.coef_
```

The **intercept** shows what would the target be when all features are at zero:

```
In [ ]: model.intercept_
```

Optional Challenge 2:

Customer churn 

Regression vs. Classification

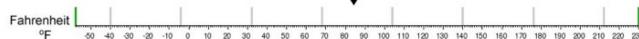


Regression

What is the temperature going to be tomorrow?

PREDICTION

84°

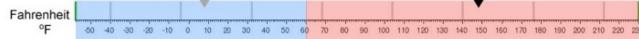


Classification

Will it be Cold or Hot tomorrow?

COLD

PREDICTION
HOT



You now have the tools

Your **turn!** 