indeed

Using Open Source Tools for Machine Learning

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Data Scientist

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Master

Ryan Born

We help people get jobs.

THIS TALK IS

- An introduction to ML
- Friendly to newcomers
- Helpful to experienced folks
- Oriented toward application
- Respectful of theory

THIS TALK IS NOT

- A substitute for a Ph. D.
- The end-all, be-all
- A detailed tutorial

Agenda

Machine learning intro

UC0: Credit card applications

UC1: Teach a computer ASL

UC2: Forecasting energy load

UC3: Use ML to find your next job

Agenda

Machine learning intro

UC0: Credit card applications

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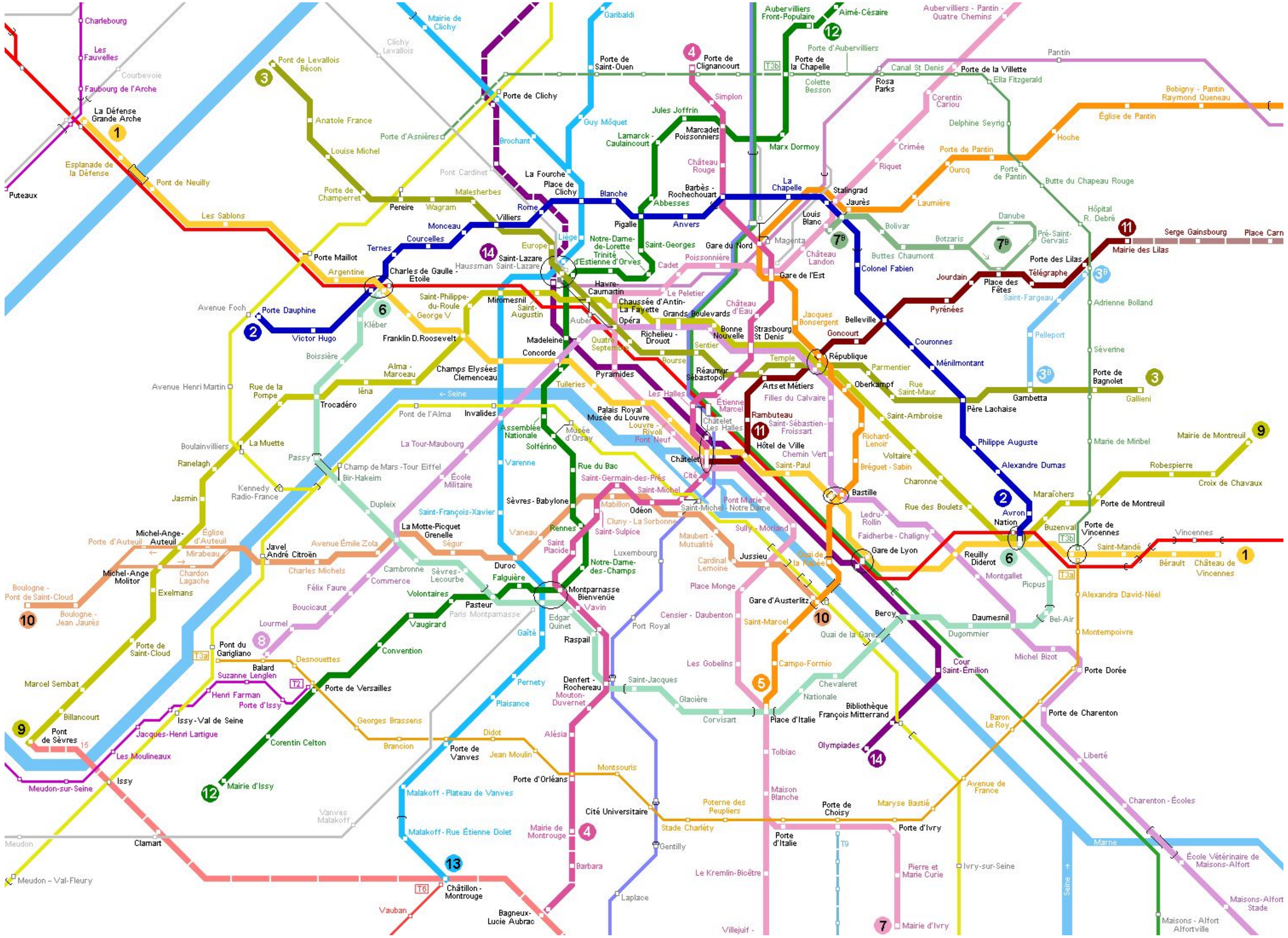
Machine learning?



urbanrail.net

Machine learning

Supervised	Unsupervised	Other stuff (lots)

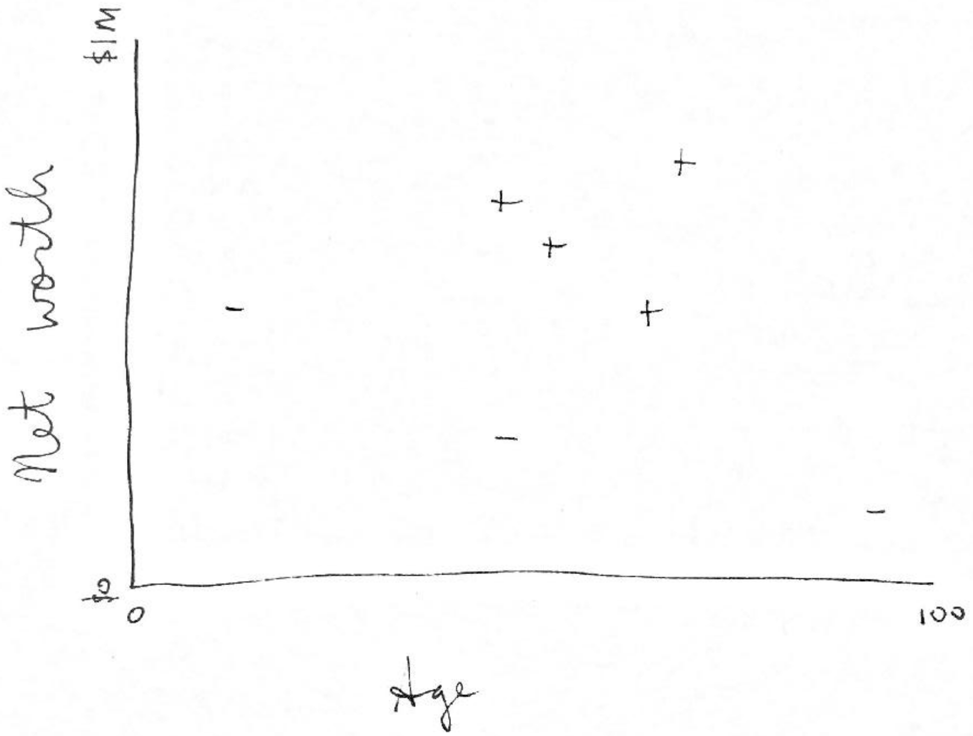
Machine learning

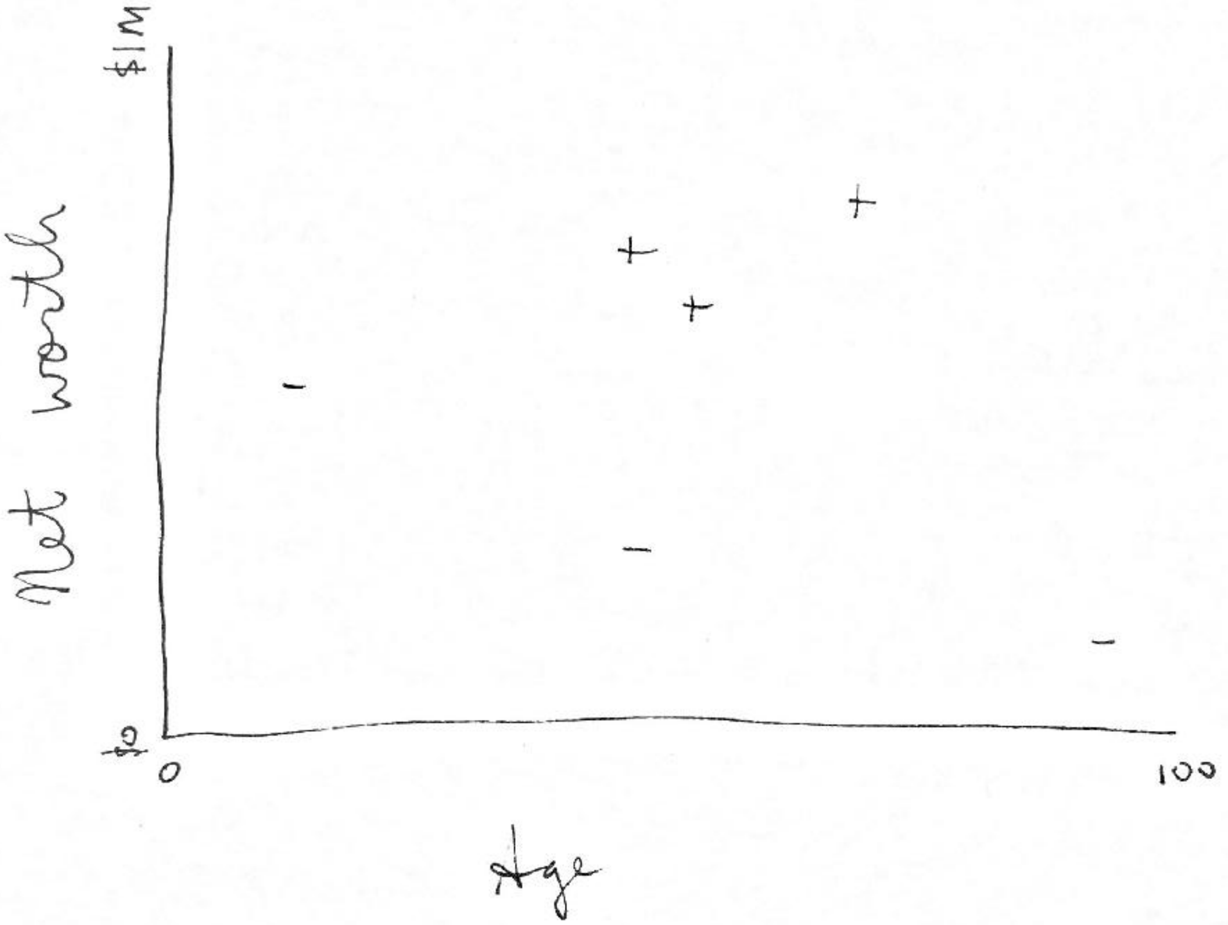
Supervised
Classification
Regression

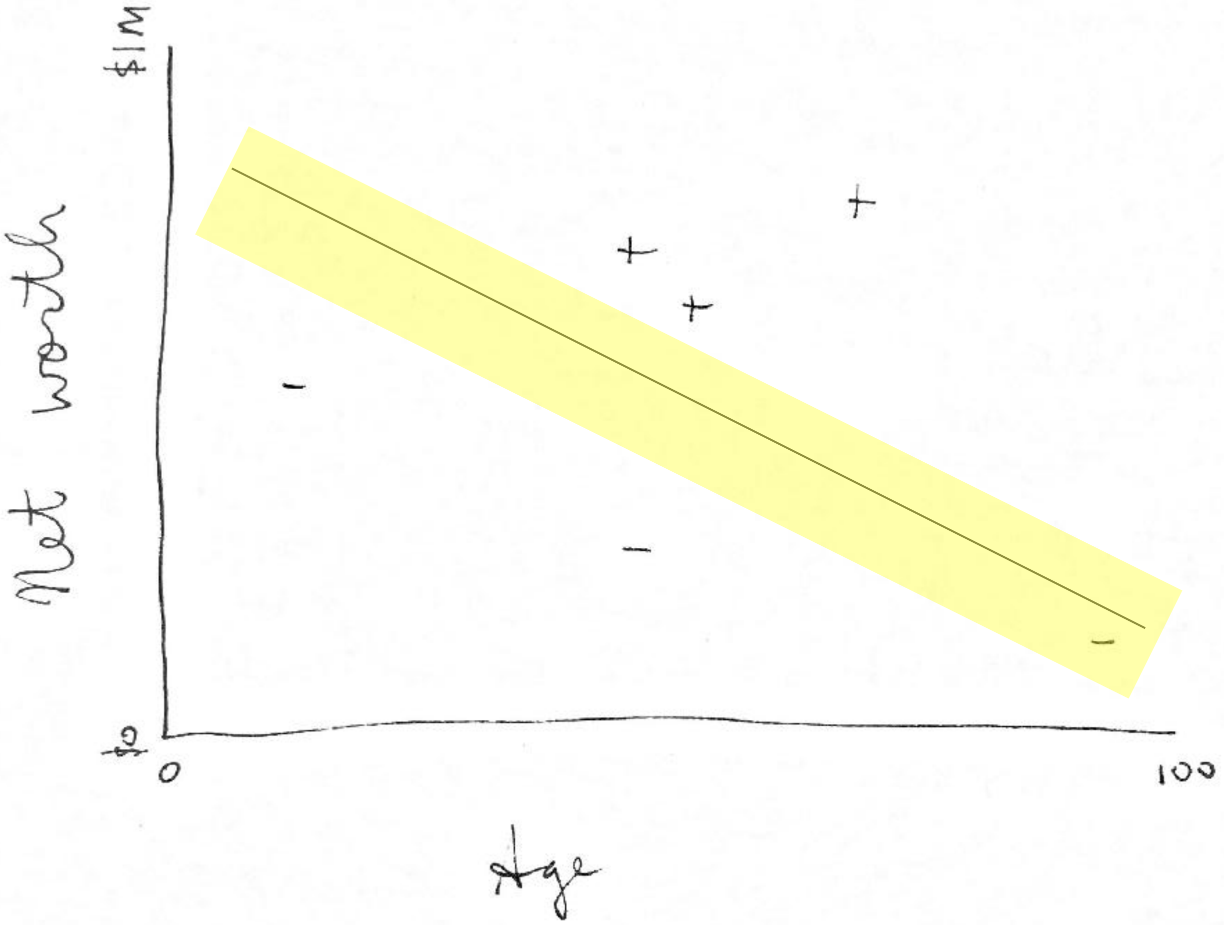
Unsupervised

Other stuff (lots)

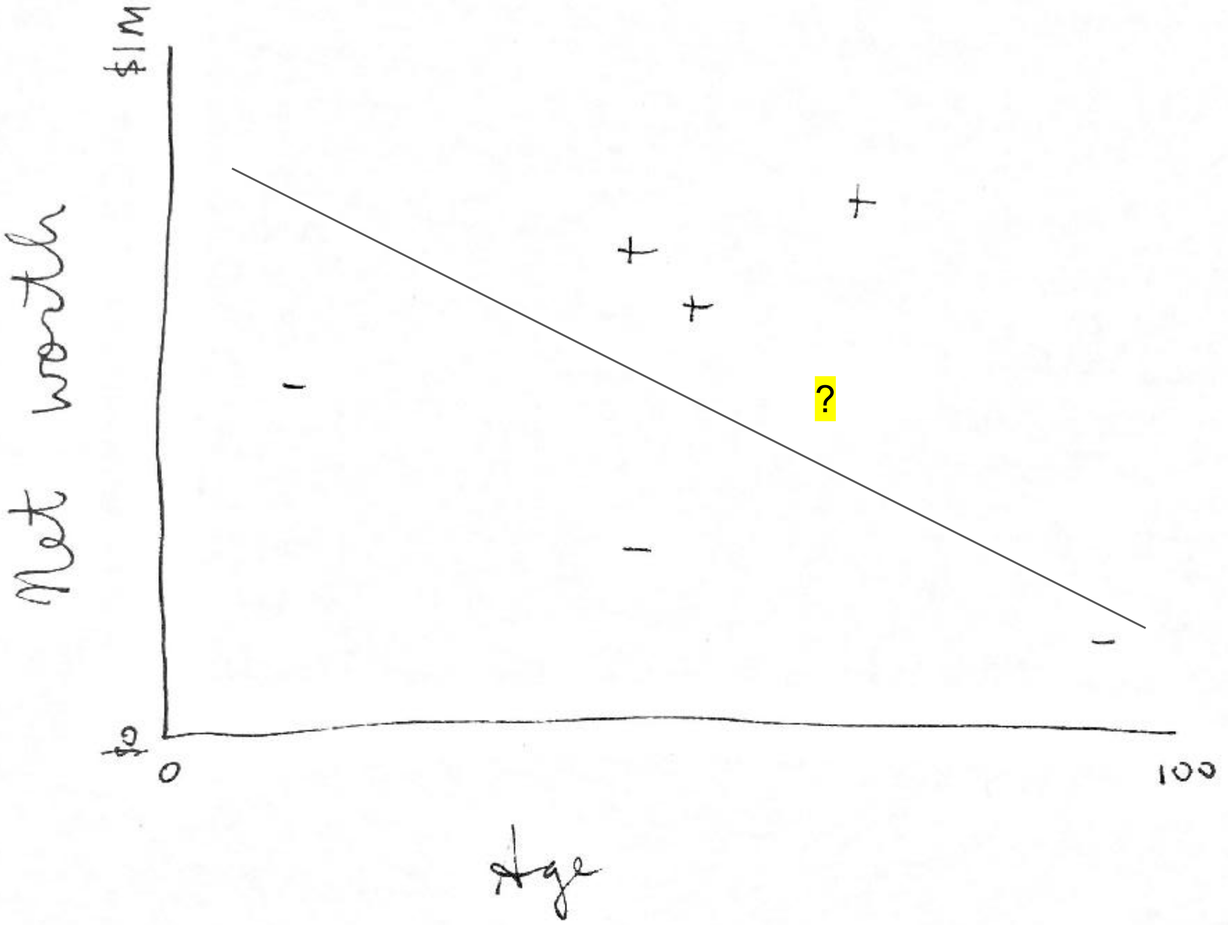
Age	Net worth	Given credit?
12.5	$500K	No
50	$250K	No
97	$90K	No
50	$750K	Yes
53	$650K	Yes
60	$500K	Yes
62	$800K	Yes

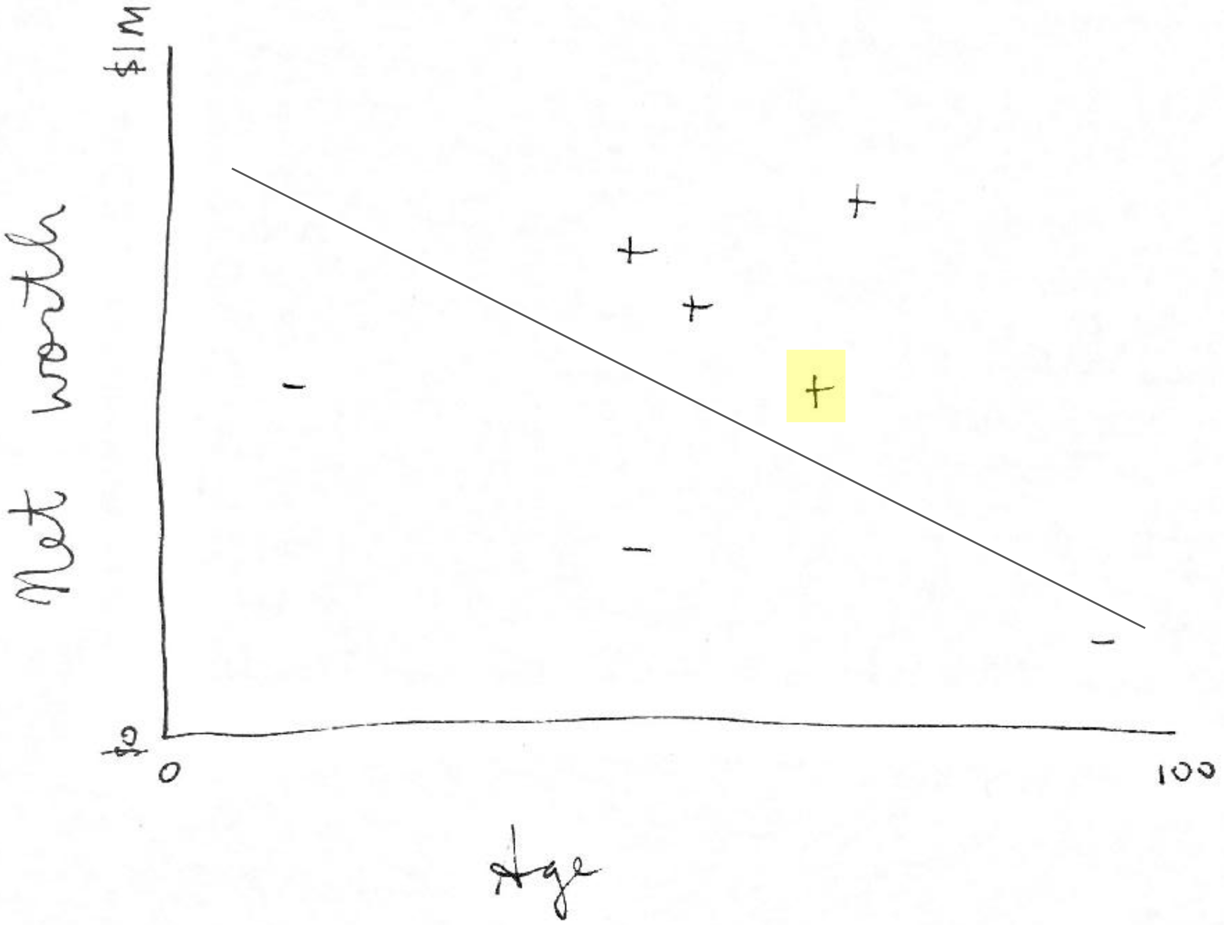



$1M
Net worth
$0
0
100
Age



$1M
Net worth
$0
0
100
Age
+
+
+
-
-
-


$1M
Net worth
$0
0
100
Age
?

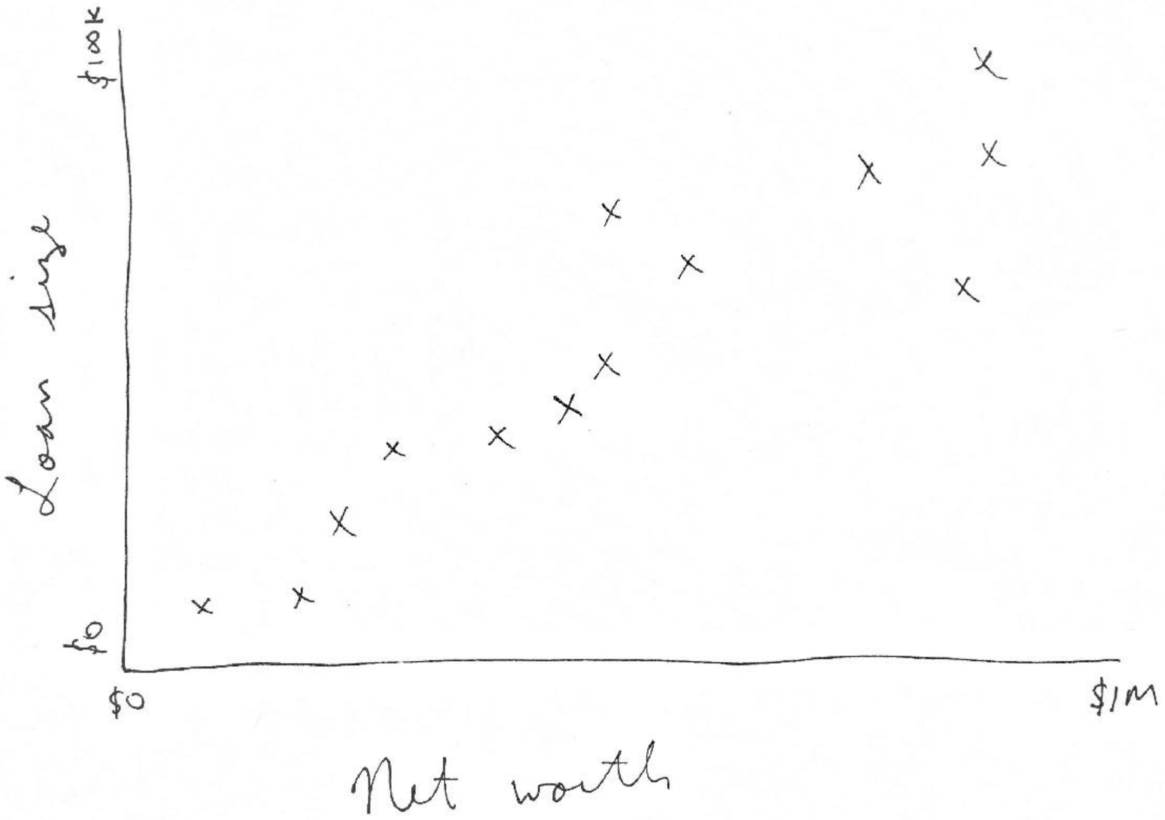

$1M
Net worth
$0
0
100
Age

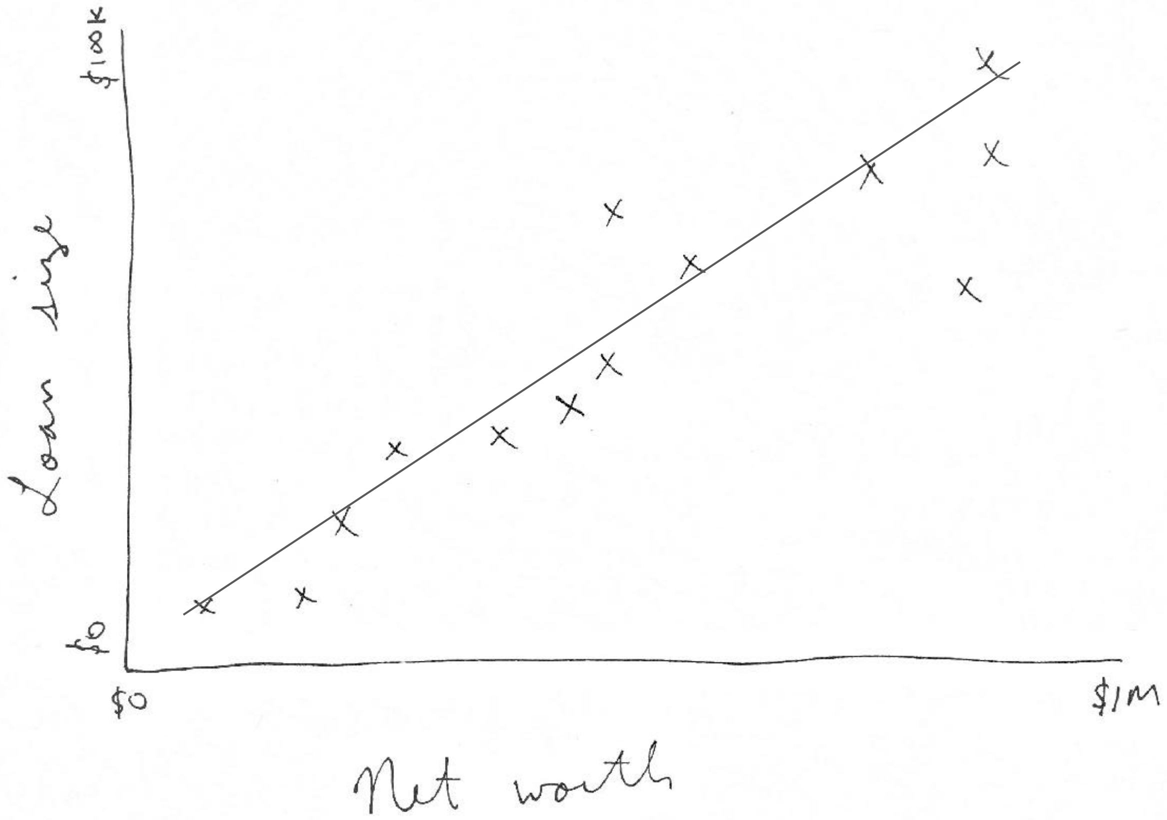
Machine learning

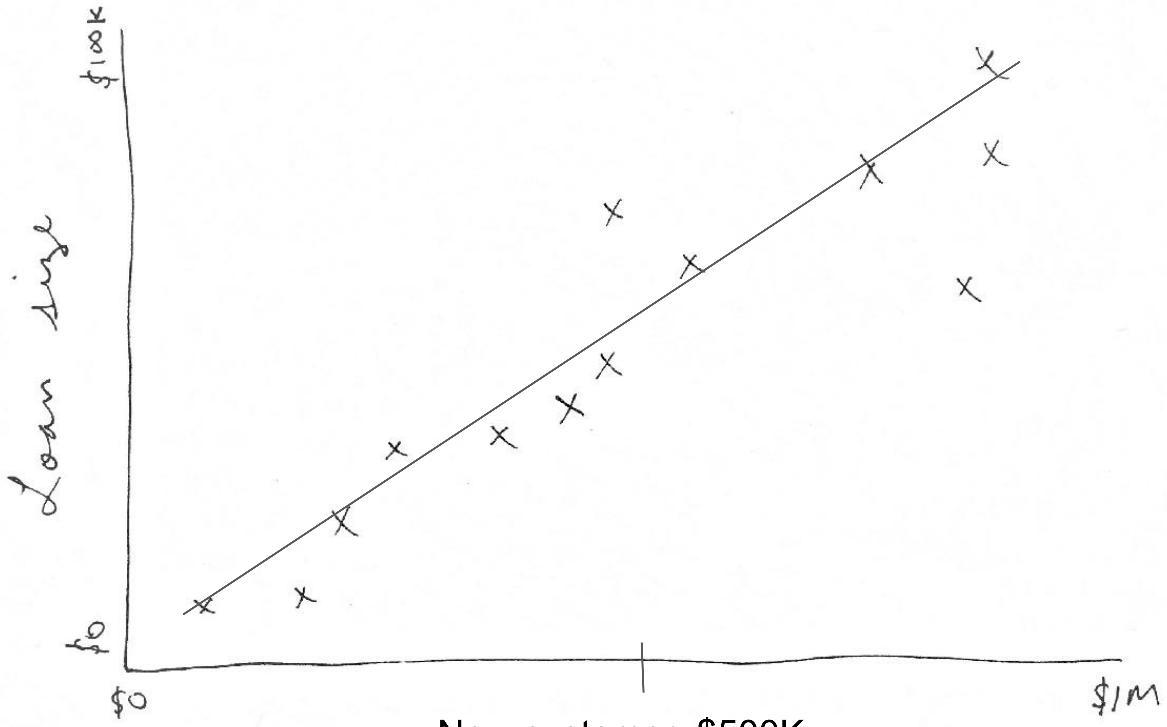
Supervised
Classification
Regression

Unsupervised

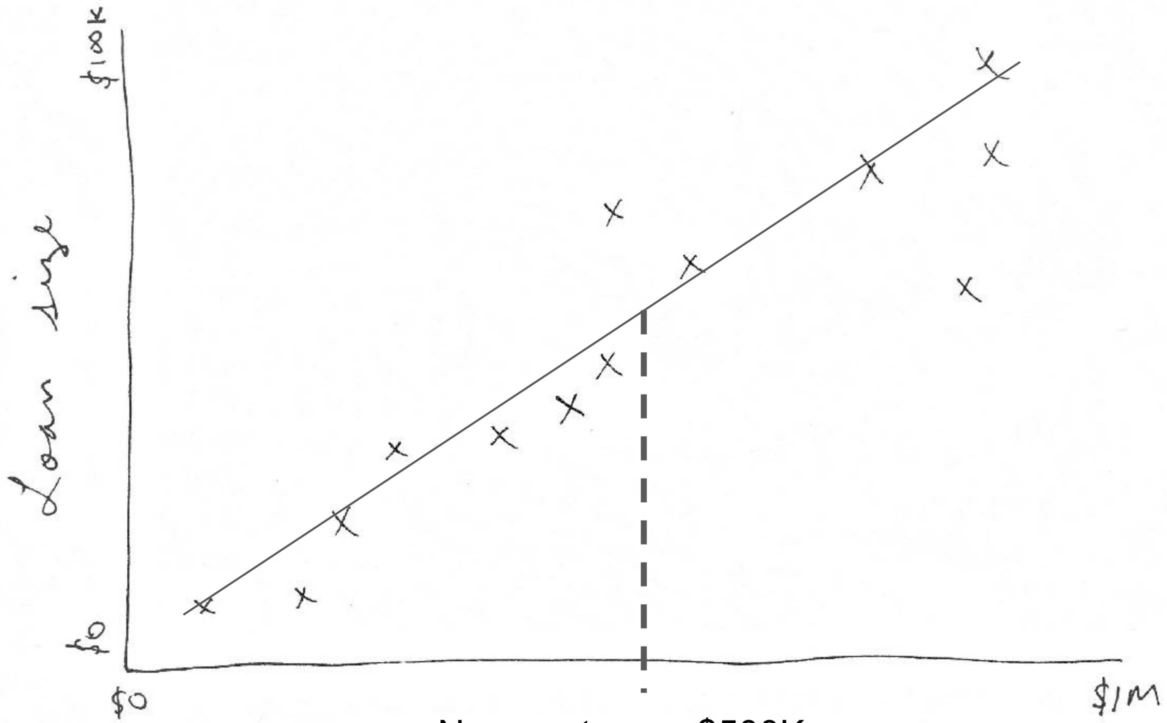
Other stuff (lots)


$100K
$0
Loan size
$0
$1M
Net worth

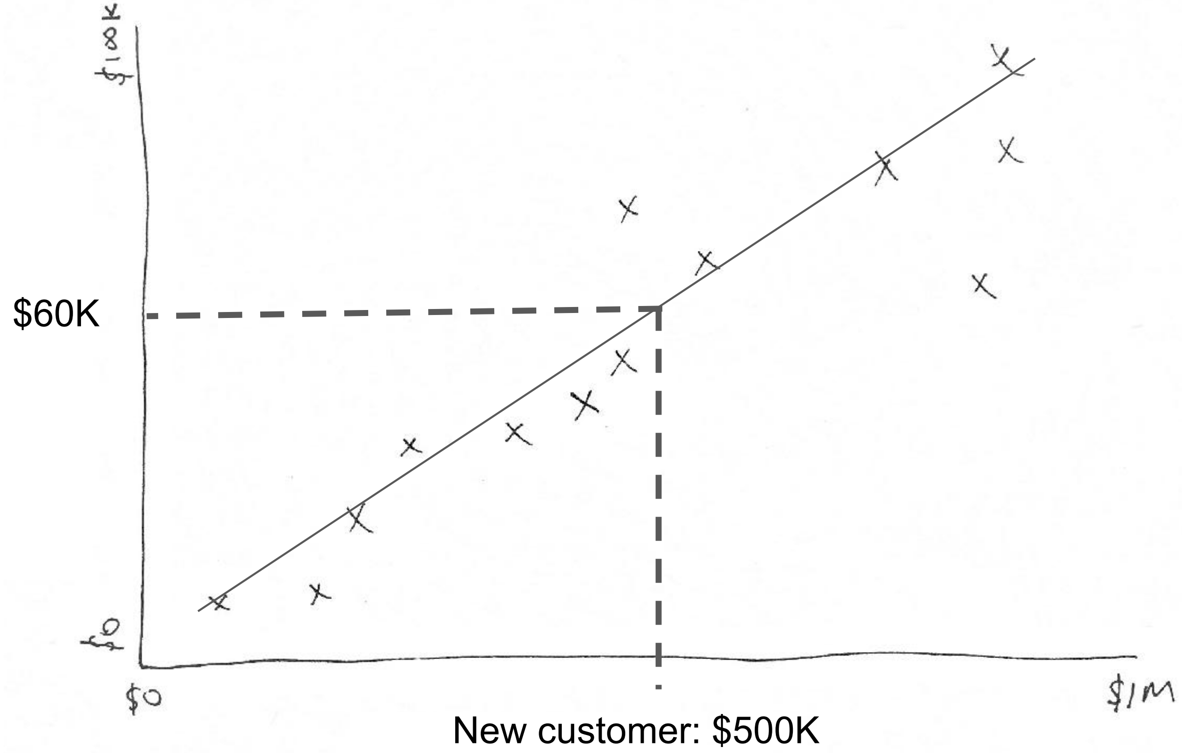

$100K
$0
Loan size
$0
$1M
Net worth



New customer: $500K



New customer: $500K

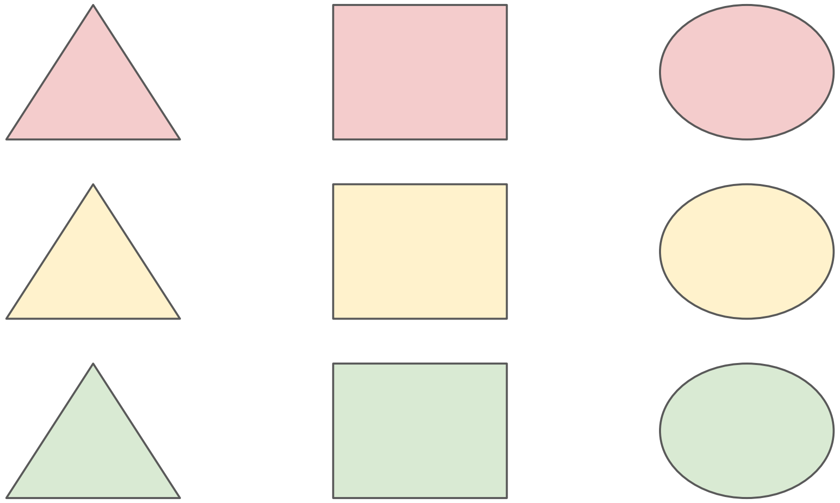

$100K
$0
$60K
$0
$1M
New customer: $500K

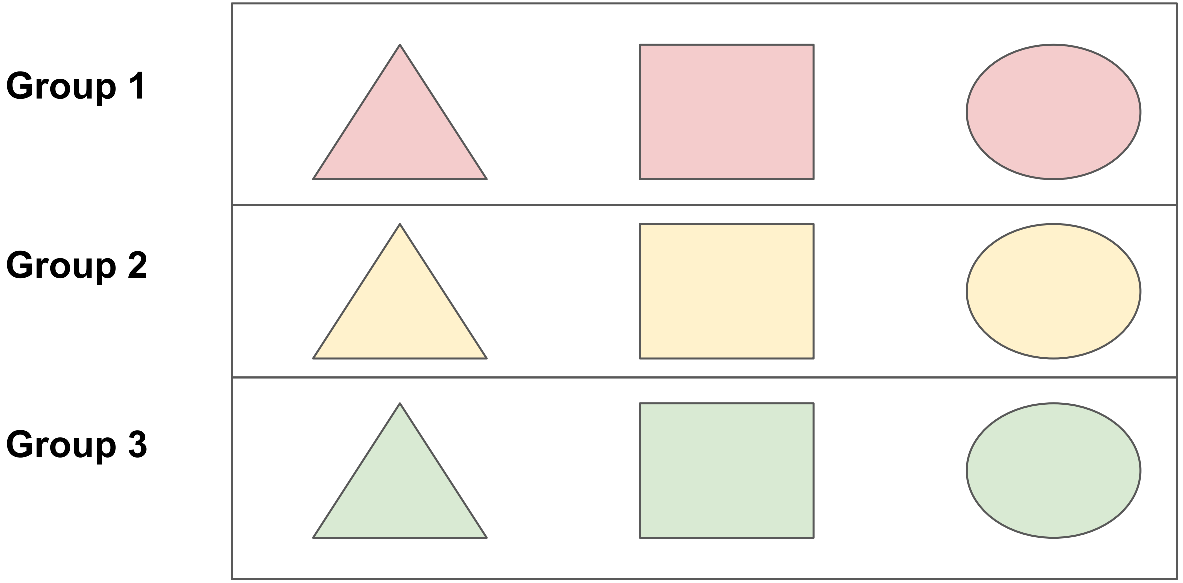
Machine learning

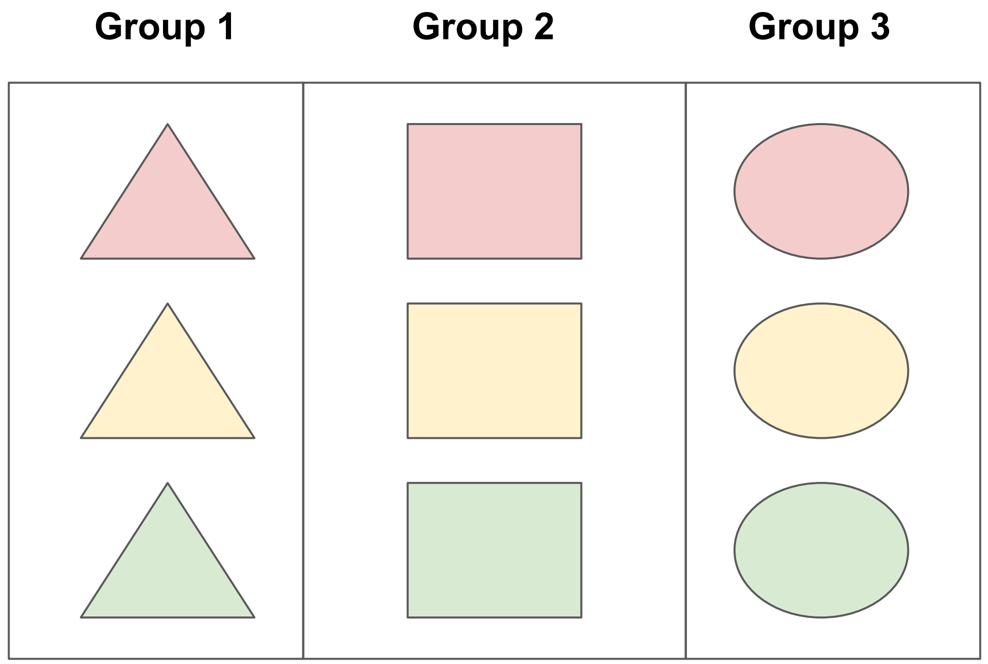
Supervised

Unsupervised
Clustering

Other stuff (lots)




Group 1
Group 2
Group 3


Group 1
Group 2
Group 3

Machine learning

Supervised

Unsupervised

Other stuff
(lots)

ML uses data to approximate something we care about

➔ Goal Find *f(x)*

ML uses data to approximate something we care about

- ➔ Goal Find *f(x)*
- ➔ **Problem** ***f(x)*** **is unknown**
  (perhaps unknowable)

ML uses data to approximate something we care about

- ➔ **Goal Find *f(x)***
- ➔ **Problem *f(x)* is unknown**
  (perhaps unknowable)
- ➔ **But we can measure points from *f(x)***
  (with noise)

ML uses data to approximate something we care about

- ➔ Goal Find *f(x)*
- ➔ Problem *f(x)* is unknown (perhaps unknowable)
- ➔ But we can measure points from *f(x)* (with noise)
- ➔ Algorithms to find a *g(x)* that approximates *f(x)*

Agenda

Machine learning intro

UC0: Credit card applications

UC1: Teach a computer ASL

UC2: Forecasting energy load

UC3: Use ML to find your next job

- What’s the problem?
- What does the data look like?
- What kind of ML problem is this?
- Solution
- Lessons learned

➔ What’s the problem?

Should we (the bank)
give this consumer a credit card?

→ What does the data look like?

Age	Net worth (K$)	Given credit?
12.5	500	No
50	250	No
62	800	Yes
50	750	Yes
53	650	Yes
60	500	Yes

→ **What kind of ML problem is this?**

➔ What kind of ML problem is this?

Classification

→ Solution

scikit learn

e1701, rpart, igraph, nnet, randomForest, caret, kernlab, ...

WEKA
The University of Waikato

➔ Solution

```
from sklearn.svm import LinearSVC

features = [(12.5, 500), (50, 250), (62, 800),
            (50, 750), (53, 650), (60, 500)]
given_credit = [False, False, True, True, True, True]

classifier = LinearSVC()
classifier.fit(features, given_credit)
classifier.predict([[63, 500]])
```

➔ Solution

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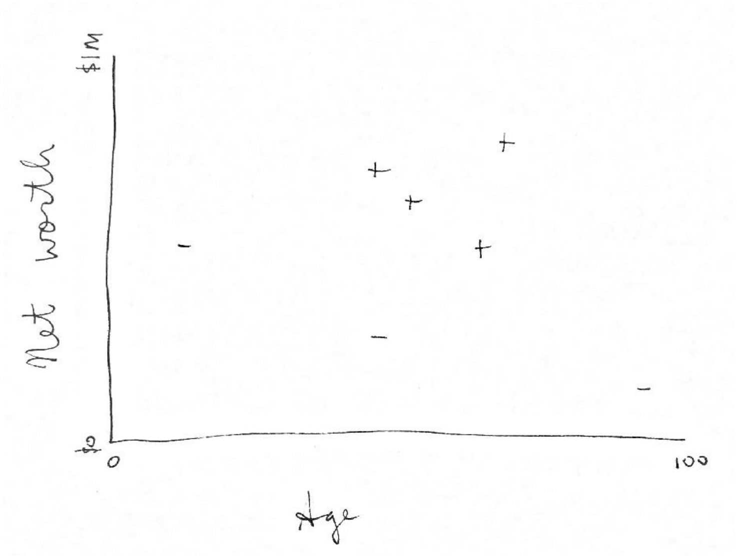

➔ Solution

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from sklearn.svm import LinearSVC

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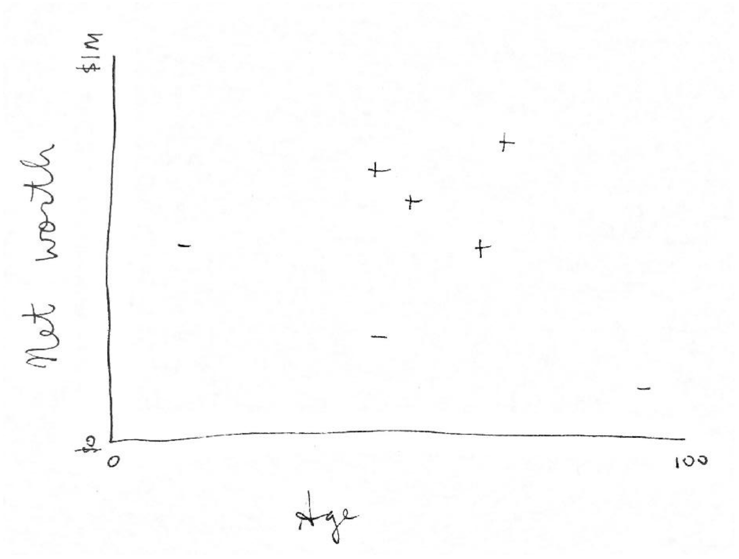

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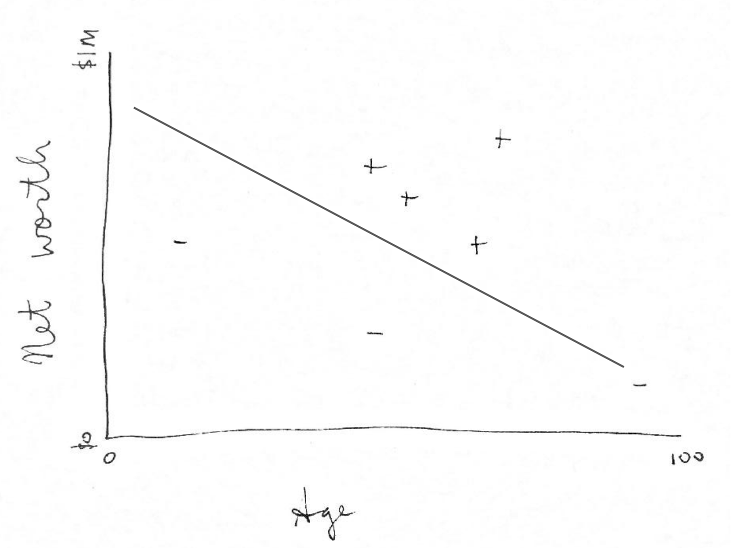

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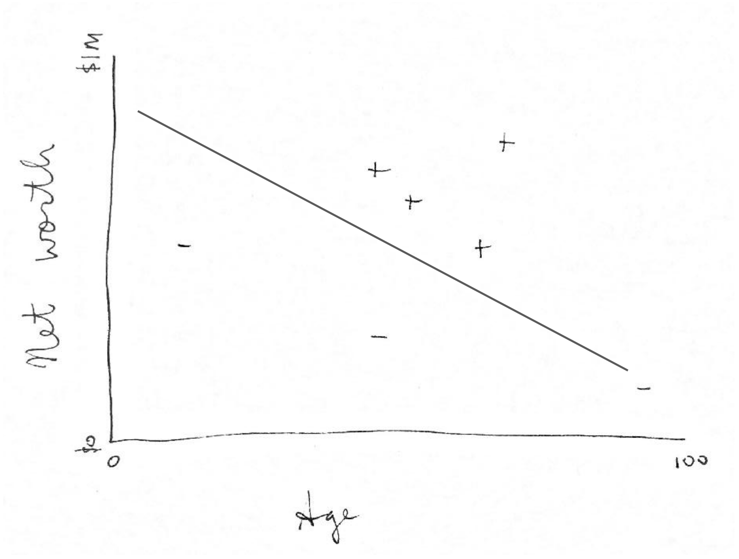
```



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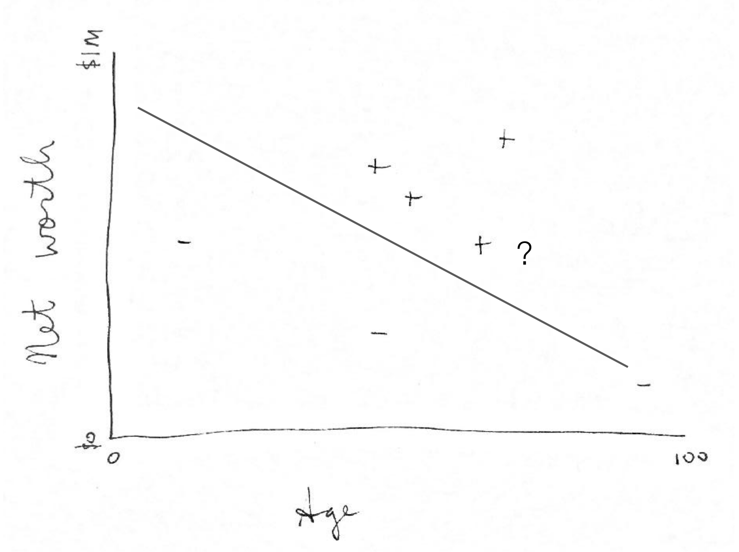

➔ Solution

```python
from sklearn.svm import LinearSVC

features = [(12.5, 500), (50, 250), (62, 800),
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given_credit = [False, False, True, True, True, True]

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```
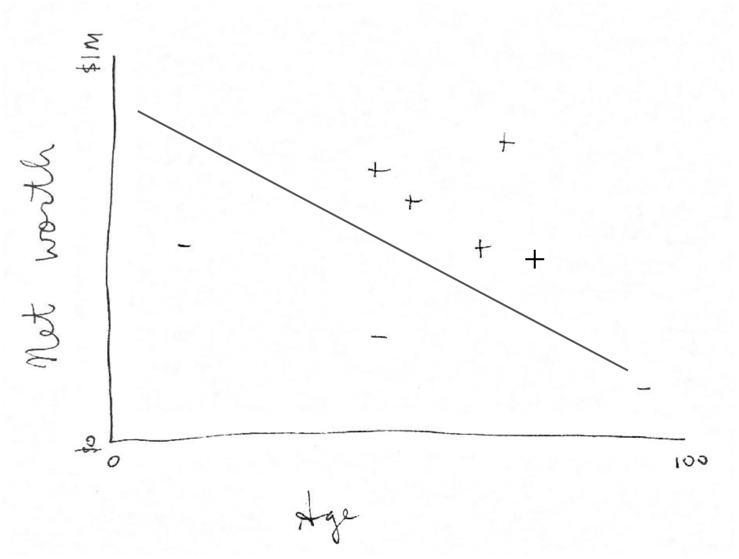
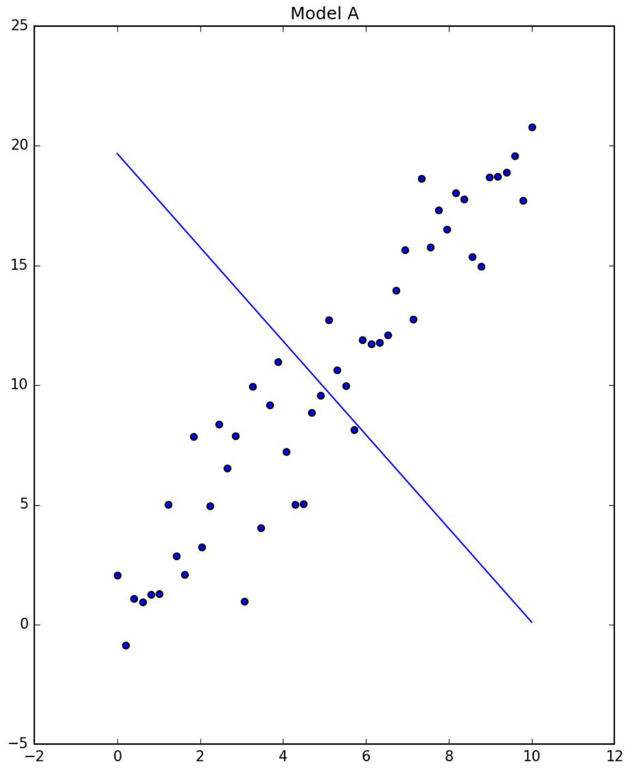
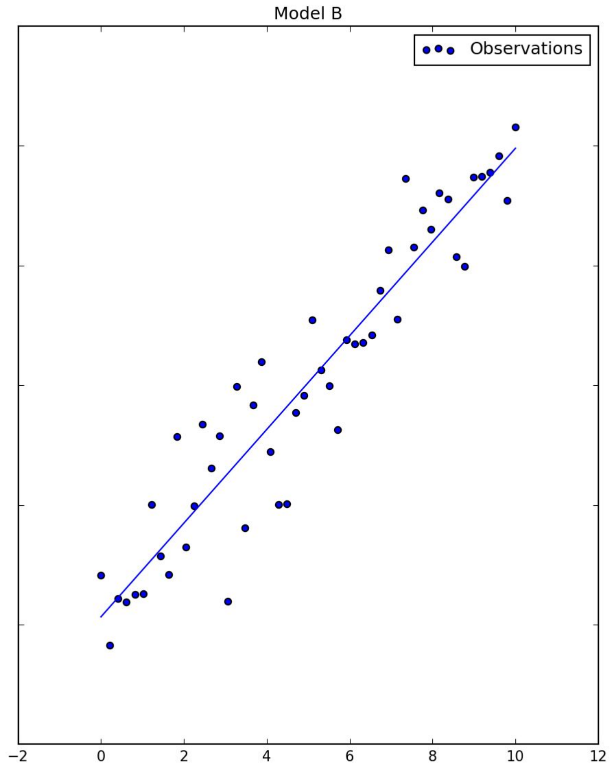



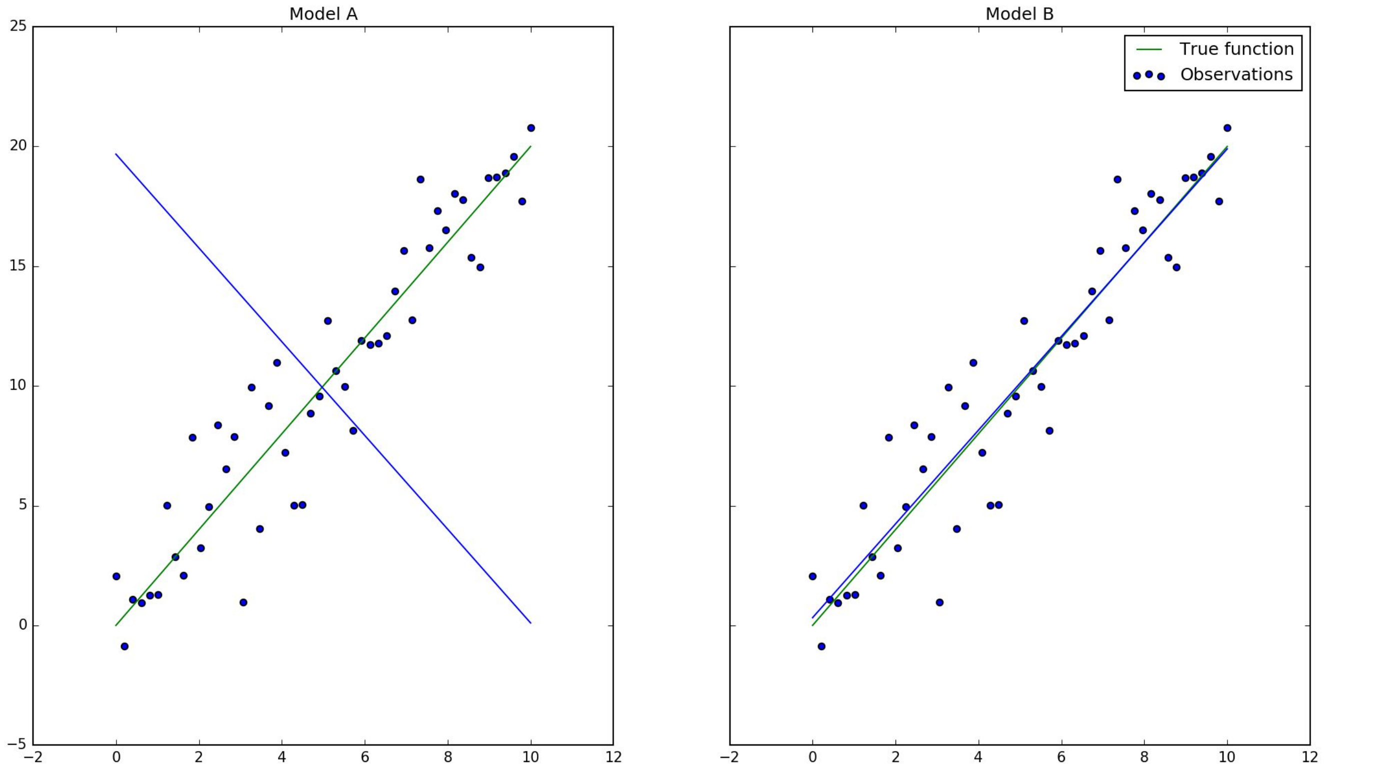
How accurate is it?

Measuring error

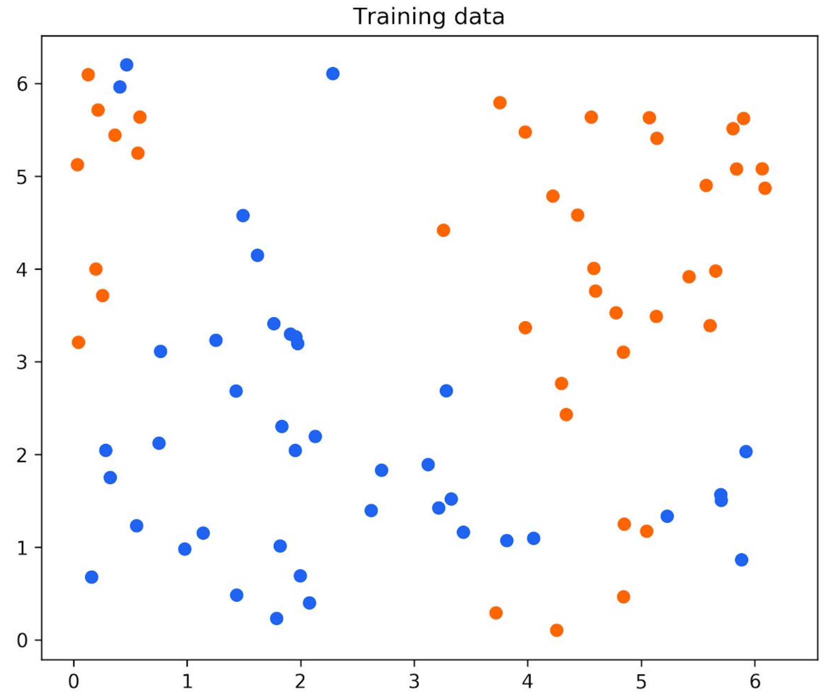


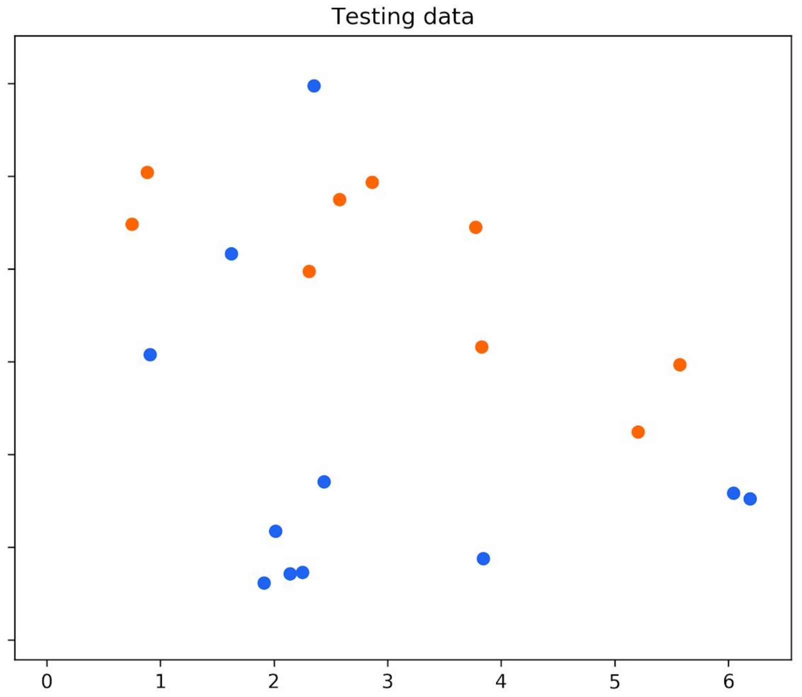


Measuring error



Randomly selected testing data allows for model evaluation



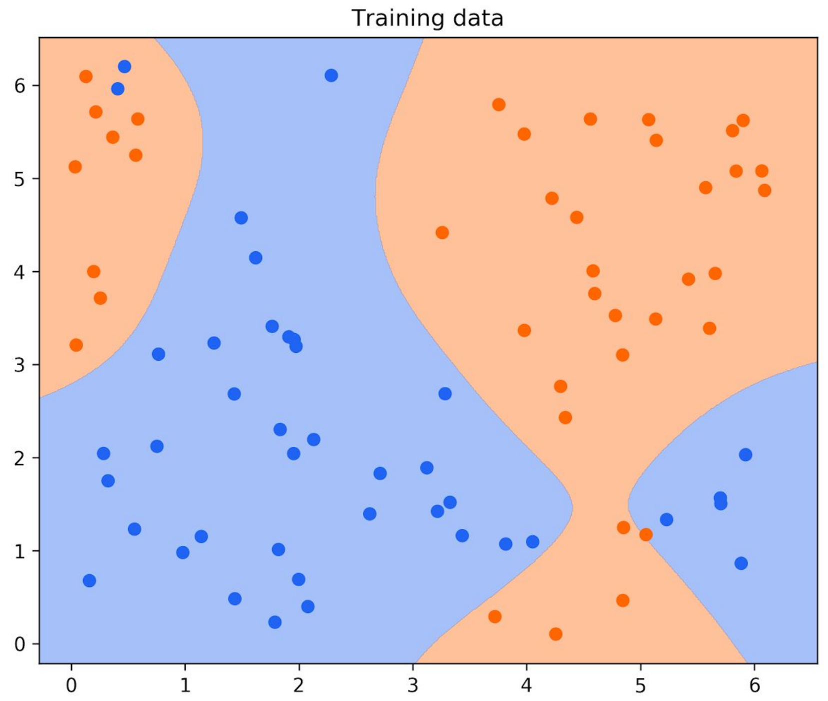


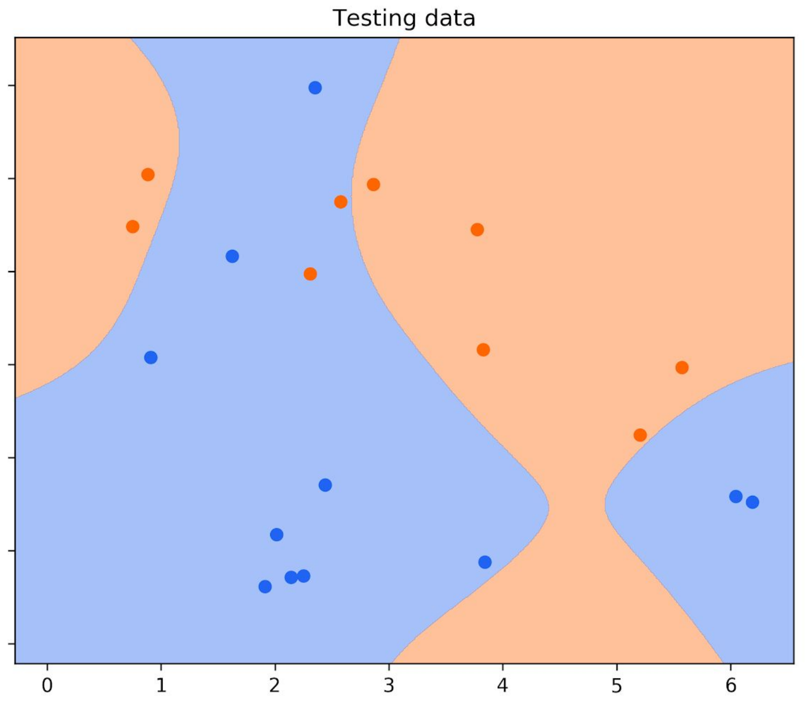
Randomly selected testing data allows for model evaluation

Training data
Testing data
0
1
2
3
4
5
6

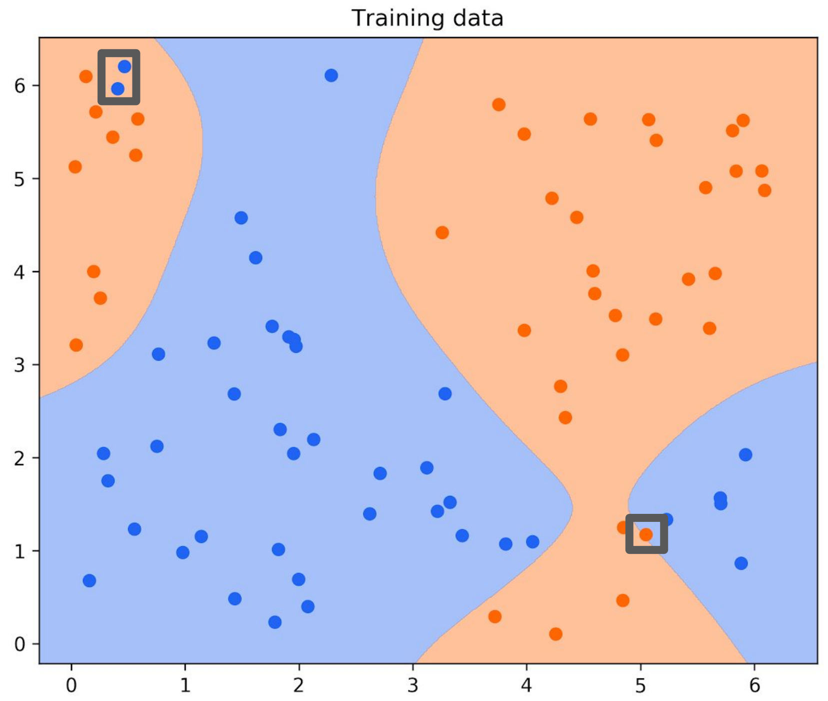
`sklearn.model_selection.train_test_split`

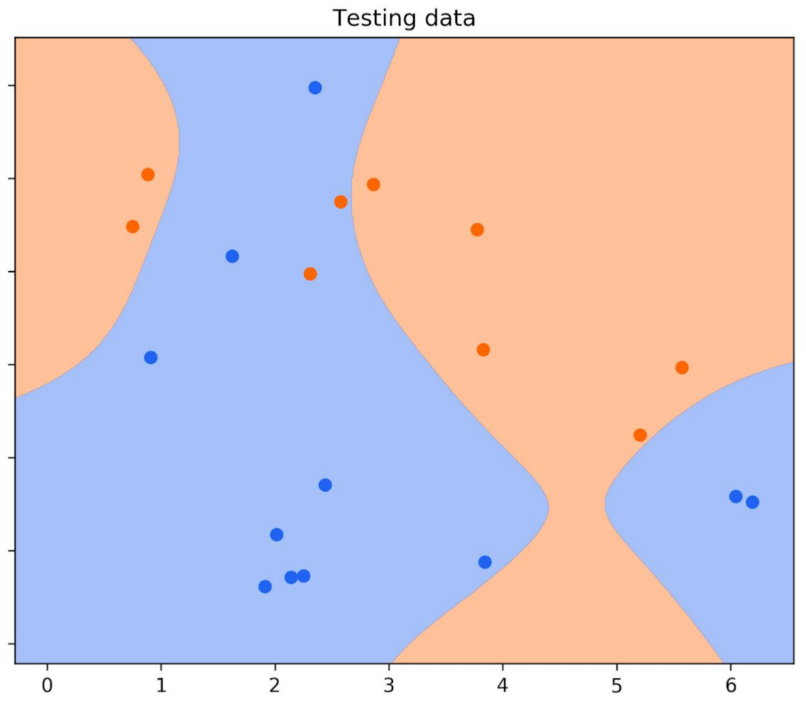
Train a model on the training data, see how it does on the testing data





Train a model on the training data, see how it does on the testing data





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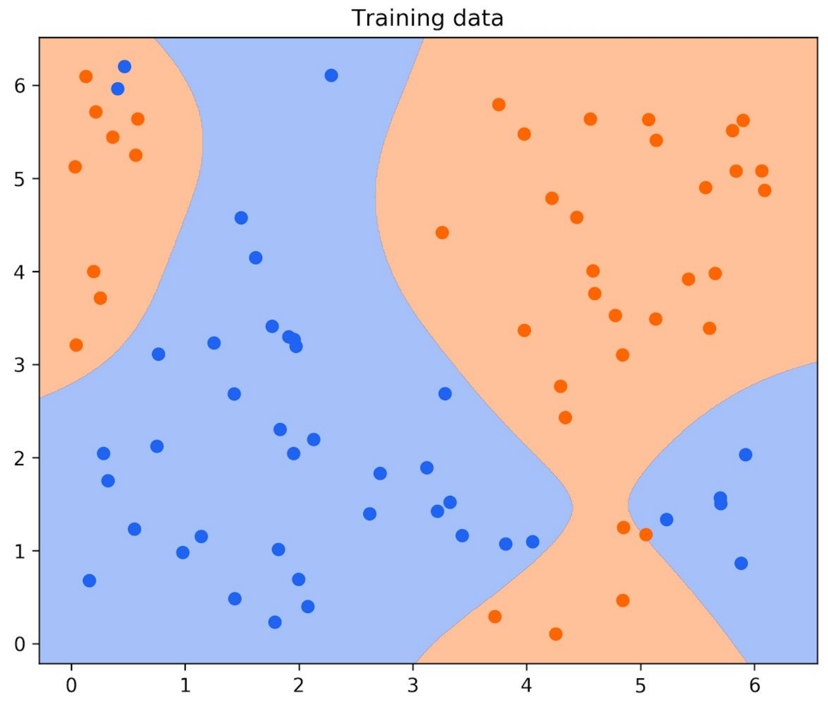
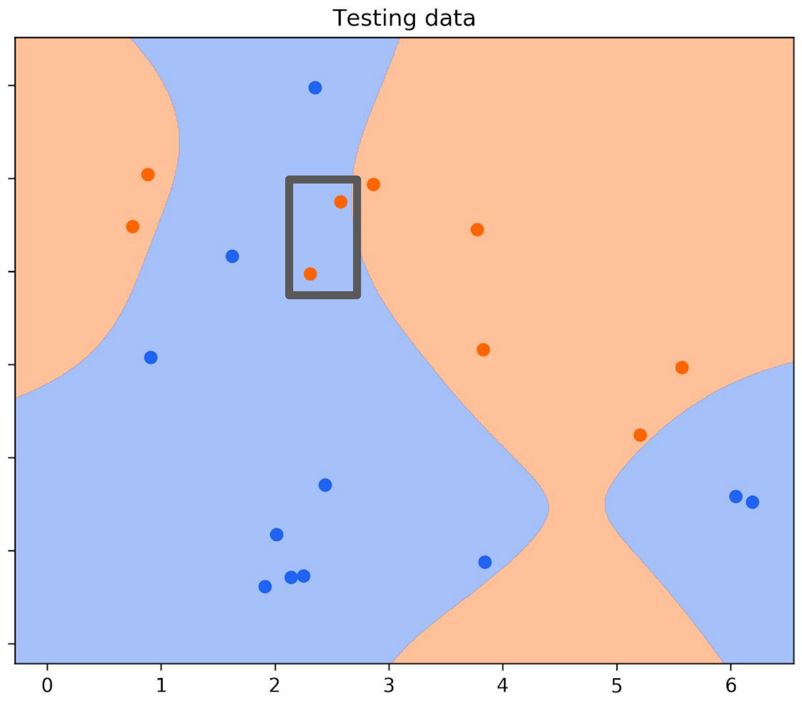




Measuring error

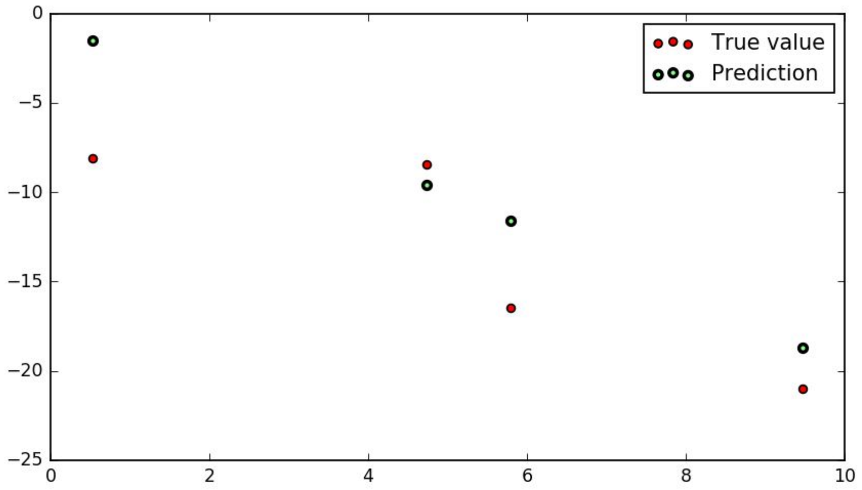
- Hold out some “testing data”
- Compare test data to prediction
- Ideally, calculate real cost

	Actually a warhead	**Actually not a warhead**
Predict a warhead	👍	Destruction of humanity
Predict not a warhead	Destruction of humanity	👍

	Actually me	**Actually not me**
Recognize fingerprint	👍	People criticize my memes for not being funny
Reject fingerprint	I get a little annoyed	👍

Defining real cost is not always possible

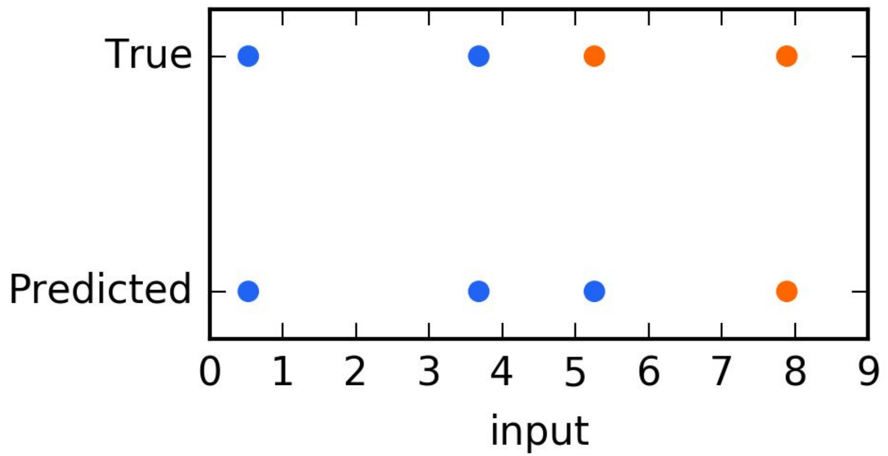
Mean squared error



Input	True	Predict	Diff	Sq. diff
0.53	-8.10	-1.51	-6.60	43.50
4.74	-8.47	-9.60	1.13	1.27
5.79	-16.45	-11.62	-4.83	23.30
9.47	-21.01	-18.70	-2.31	5.34

(43.5 + 1.27 + 23.3 + 5.34) / 4 = 18.35

Classification error



Input	True	Predict	Error?
0.53	1	1	0
3.68	1	1	0
5.26	0	1	1
7.89	0	0	0

UC0: LESSONS LEARNED

- This stuff is pretty neat
- Testing data enables evaluation

Agenda

Machine learning intro

UC0: Credit card applications

UC1: Teach a computer ASL

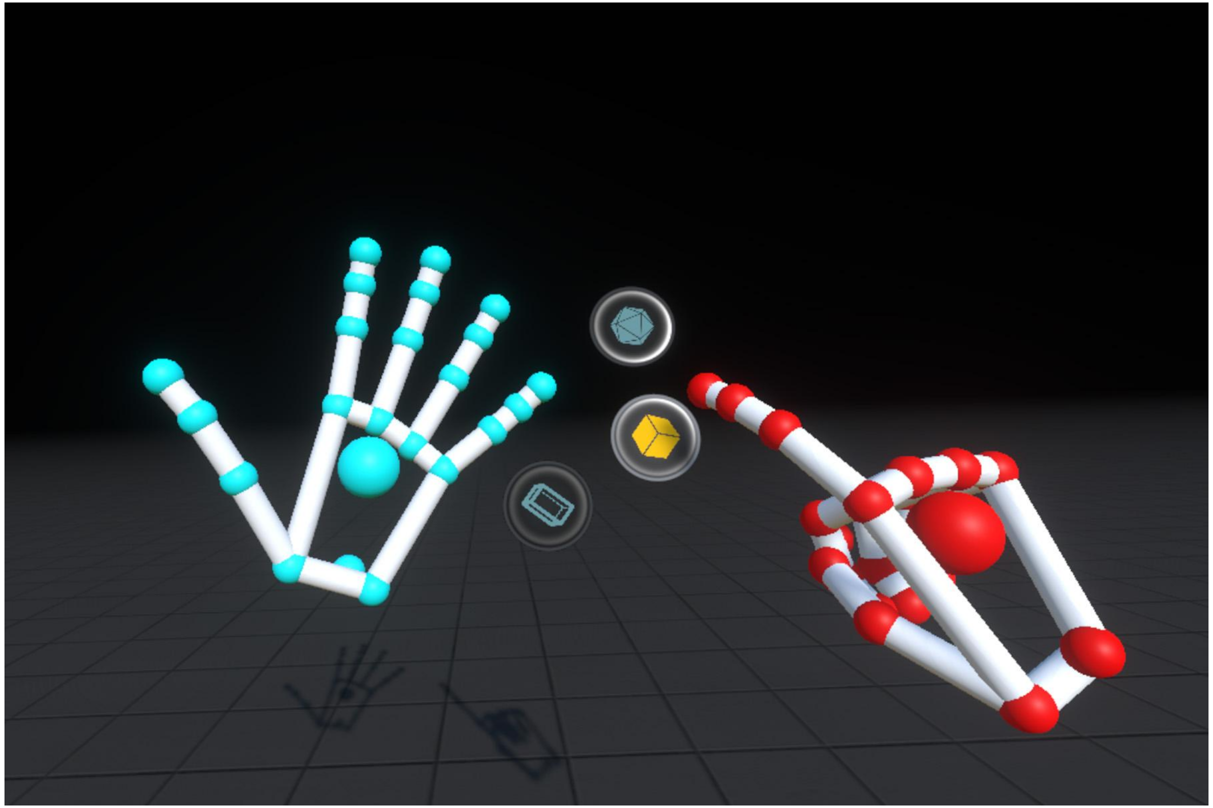
UC2: Forecasting energy load

UC3: Use ML to find your next job

➔ What’s the problem?

I don’t know sign language.

khawkins04



→ What does the data look like?

joint1_x	joint1_y	joint1_z	...	joint20_x	joint20_y	joint20_z	sign
-14.24845886	-11.23913574	47.79299927	...	39.12654877	-20.38291168	-67.37110138	a
-14.24845886	-11.23913574	47.79299927	...	39.12654877	-20.38291168	-67.37110138	a
-14.24845886	-11.23913574	47.79299927	...	39.12654877	-20.38291168	-67.37110138	a
-14.66805267	-12.86016846	47.25432587	...	39.19580078	-18.27232361	-68.12595367	a
-6.099303246	3.211929321	-21.70319366	...	1.87420845	11.96398926	-98.45552063	b
-5.093156815	2.45741272	-22.05827522	...	6.529464722	14.67698669	-97.91105652	b
32.73310089	-1.139434814	-12.70455551	...	8.51625061	18.76667786	-97.07907867	b
33.09098053	1.941070557	-11.63526344	...	10.23889732	31.46665955	-93.68971252	b
-23.29023552	-0.6312103271	-21.13870239	...	14.70001984	23.49594116	-95.80595398	b
32.82236862	-1.860855103	-12.38504791	...	10.76865768	19.6521759	-96.92489624	b

➔ **What kind of ML problem is this?**

➔ What kind of ML problem is this?

Classification

Solution

Choose a model

- Split data into training, testing
- Train a bunch of models on training data
- Evaluate them on test data
- Select the best one

→ Solution

Build an application

- → Keyboard… not so great
- → But! It’s good enough to make an educational game

Great job! Now try "x".

ssaamm/sign-language-tutor

UC1: LESSONS LEARNED

- Define the problem
- Limit scope
- Model selection
- More than the model

Agenda

Machine learning intro

UC0: Credit card applications

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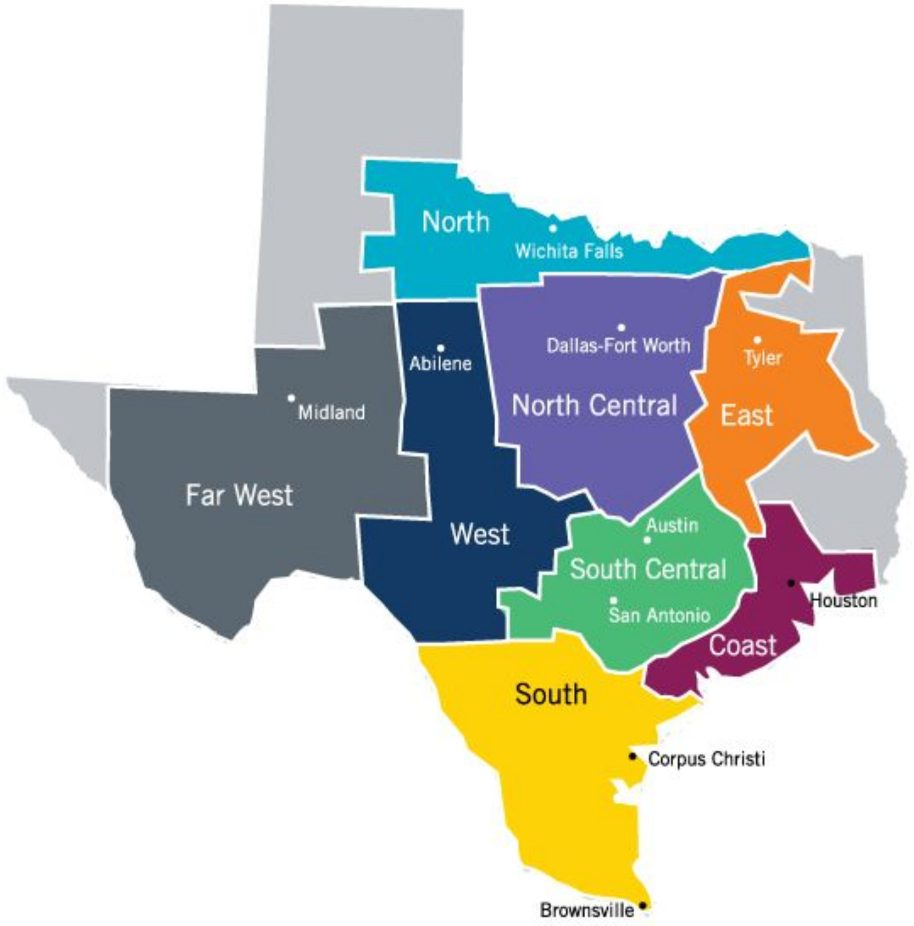
UC2: Forecasting energy load

UC3: Use ML to find your next job

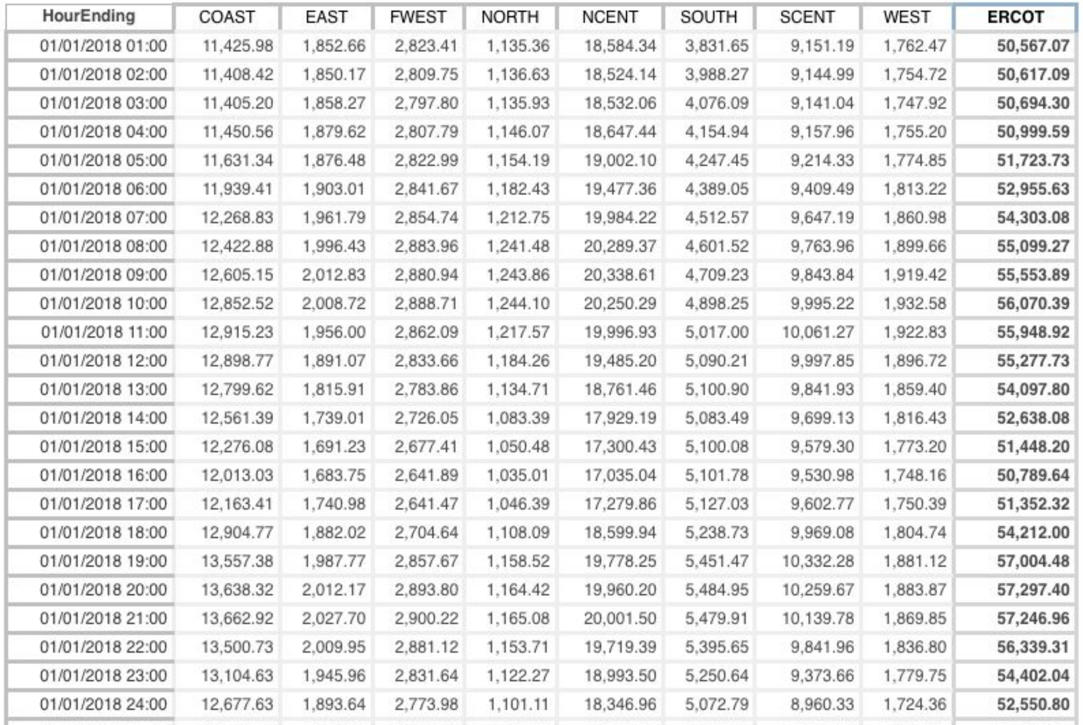
➔ What’s the problem?

Must know when to schedule energy production


North
Wichita Falls
Abilene
Dallas-Fort Worth
Tyler
Midland
North Central
East
Far West
West
Austin
South Central
San Antonio
Houston
Coast
South
Corpus Christi
Brownsville

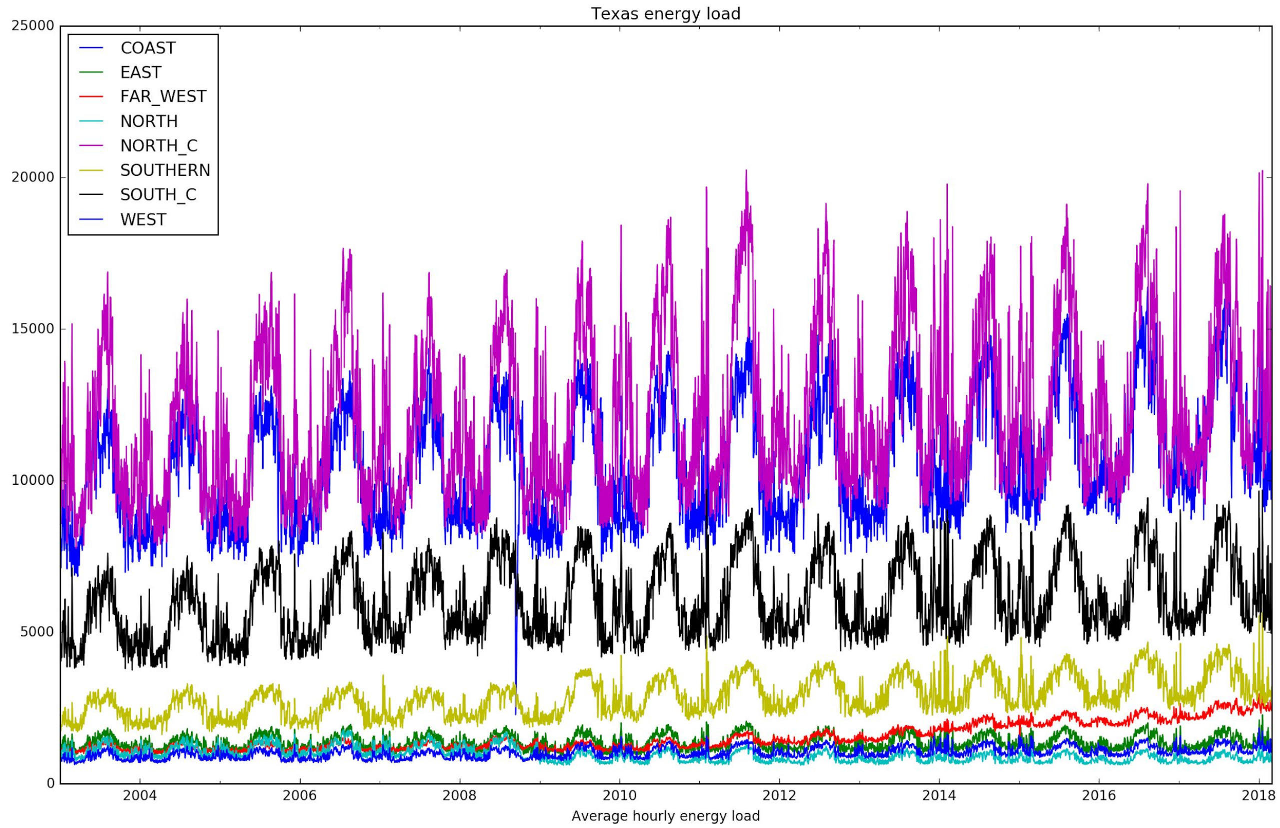
ercot

➔ What does the data look like?



HourEnding	COAST	EAST	FWEST	NORTH	NCENT	SOUTH	SCENT	WEST	ERCOT
01/01/2018 01:00	11,425.98	1,852.66	2,823.41	1,135.36	18,584.34	3,831.65	9,151.19	1,762.47	**50,567.07**
01/01/2018 02:00	11,408.42	1,850.17	2,809.75	1,136.63	18,524.14	3,988.27	9,144.99	1,754.72	**50,617.09**
01/01/2018 03:00	11,405.20	1,858.27	2,797.80	1,135.93	18,532.06	4,076.09	9,141.04	1,747.92	**50,694.30**
01/01/2018 04:00	11,450.56	1,879.62	2,807.79	1,146.07	18,647.44	4,154.94	9,157.96	1,755.20	**50,999.59**
01/01/2018 05:00	11,631.34	1,876.48	2,822.99	1,154.19	19,002.10	4,247.45	9,214.33	1,774.85	**51,723.73**
01/01/2018 06:00	11,939.41	1,903.01	2,841.67	1,182.43	19,477.36	4,389.05	9,409.49	1,813.22	**52,955.63**
01/01/2018 07:00	12,268.83	1,961.79	2,854.74	1,212.75	19,984.22	4,512.57	9,647.19	1,860.98	**54,303.08**
01/01/2018 08:00	12,422.88	1,996.43	2,883.96	1,241.48	20,289.37	4,601.52	9,763.96	1,899.66	**55,099.27**
01/01/2018 09:00	12,605.15	2,012.83	2,880.94	1,243.86	20,338.61	4,709.23	9,843.84	1,919.42	**55,553.89**
01/01/2018 10:00	12,852.52	2,008.72	2,888.71	1,244.10	20,250.29	4,898.25	9,995.22	1,932.58	**56,070.39**
01/01/2018 11:00	12,915.23	1,956.00	2,862.09	1,217.57	19,996.93	5,017.00	10,061.27	1,922.83	**55,948.92**
01/01/2018 12:00	12,898.77	1,891.07	2,833.66	1,184.26	19,485.20	5,090.21	9,997.85	1,896.72	**55,277.73**
01/01/2018 13:00	12,799.62	1,815.91	2,783.86	1,134.71	18,761.46	5,100.90	9,841.93	1,859.40	**54,097.80**
01/01/2018 14:00	12,561.39	1,739.01	2,726.05	1,083.39	17,929.19	5,083.49	9,699.13	1,816.43	**52,638.08**
01/01/2018 15:00	12,276.08	1,691.23	2,677.41	1,050.48	17,300.43	5,100.08	9,579.30	1,773.20	**51,448.20**
01/01/2018 16:00	12,013.03	1,683.75	2,641.89	1,035.01	17,035.04	5,101.78	9,530.98	1,748.16	**50,789.64**
01/01/2018 17:00	12,163.41	1,740.98	2,641.47	1,046.39	17,279.86	5,127.03	9,602.77	1,750.39	**51,352.32**
01/01/2018 18:00	12,904.77	1,882.02	2,704.64	1,108.09	18,599.94	5,238.73	9,969.08	1,804.74	**54,212.00**
01/01/2018 19:00	13,557.38	1,987.77	2,857.67	1,158.52	19,778.25	5,451.47	10,332.28	1,881.12	**57,004.48**
01/01/2018 20:00	13,638.32	2,012.17	2,893.80	1,164.42	19,960.20	5,484.95	10,259.67	1,883.87	**57,297.40**
01/01/2018 21:00	13,662.92	2,027.70	2,900.22	1,165.08	20,001.50	5,479.91	10,139.78	1,869.85	**57,246.96**
01/01/2018 22:00	13,500.73	2,009.95	2,881.12	1,153.71	19,719.39	5,395.65	9,841.96	1,836.80	**56,339.31**
01/01/2018 23:00	13,104.63	1,945.96	2,831.64	1,122.27	18,993.50	5,250.64	9,373.66	1,779.75	**54,402.04**
01/01/2018 24:00	12,677.63	1,893.64	2,773.98	1,101.11	18,346.96	5,072.79	8,960.33	1,724.36	**52,550.80**

➔ What does the data look like?

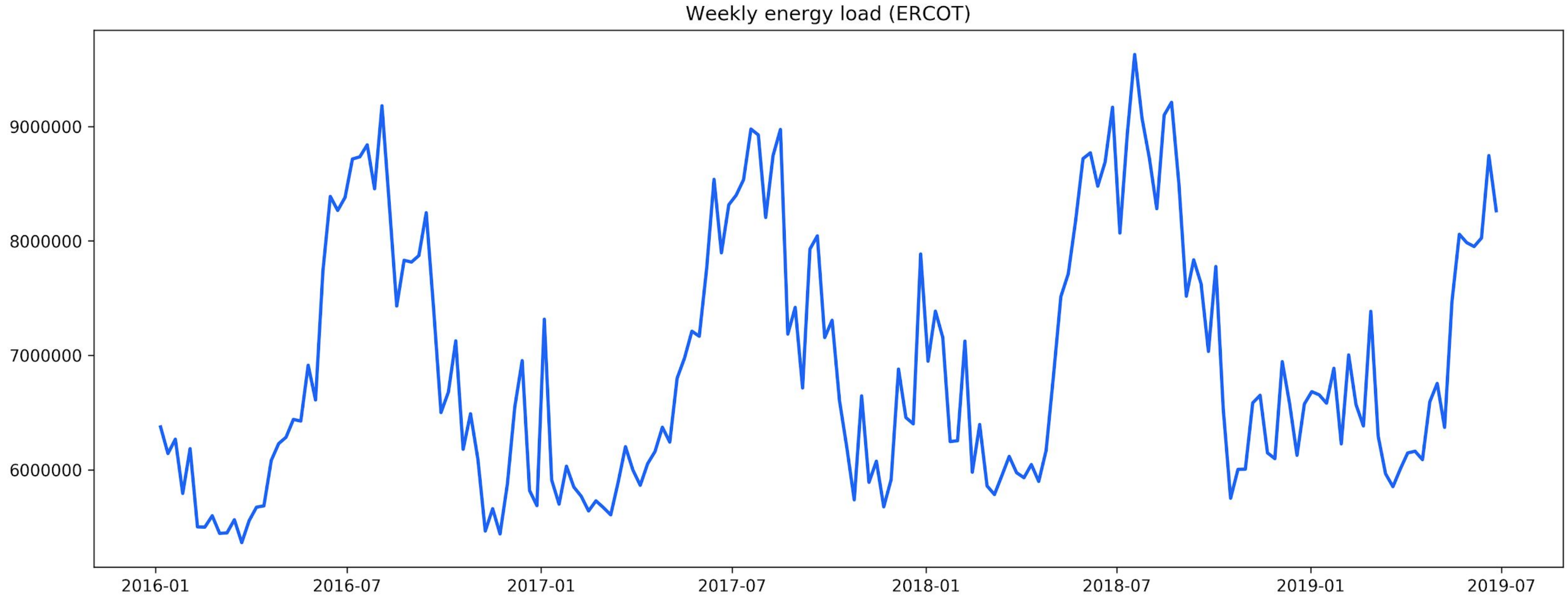


- ➔ **What kind of ML problem is this?**

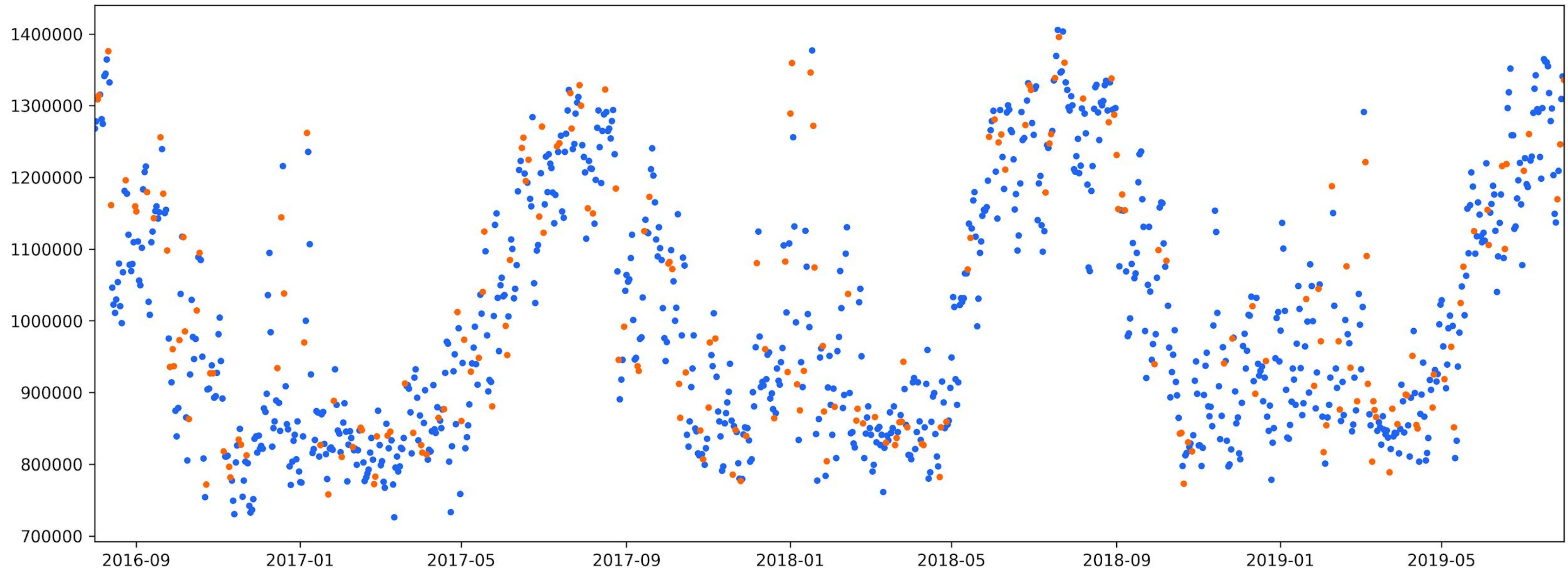
➔ What kind of ML problem is this?

Regression

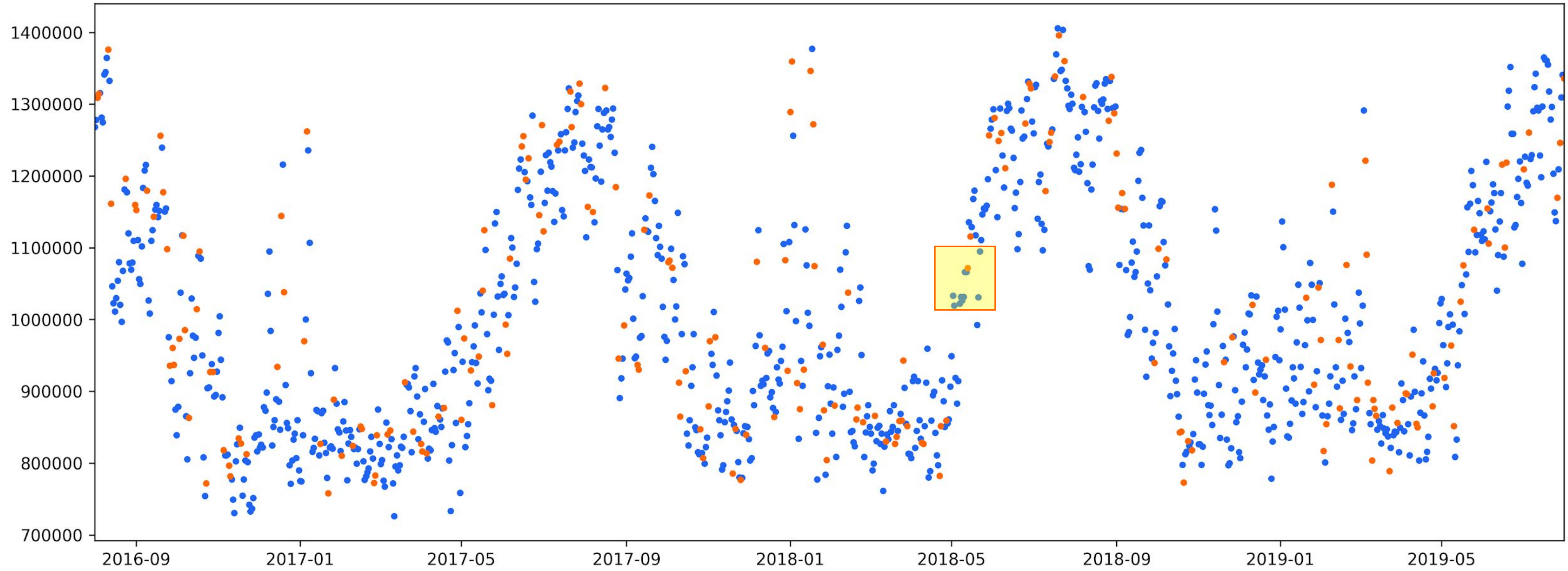
Time series data exhibits seasonality



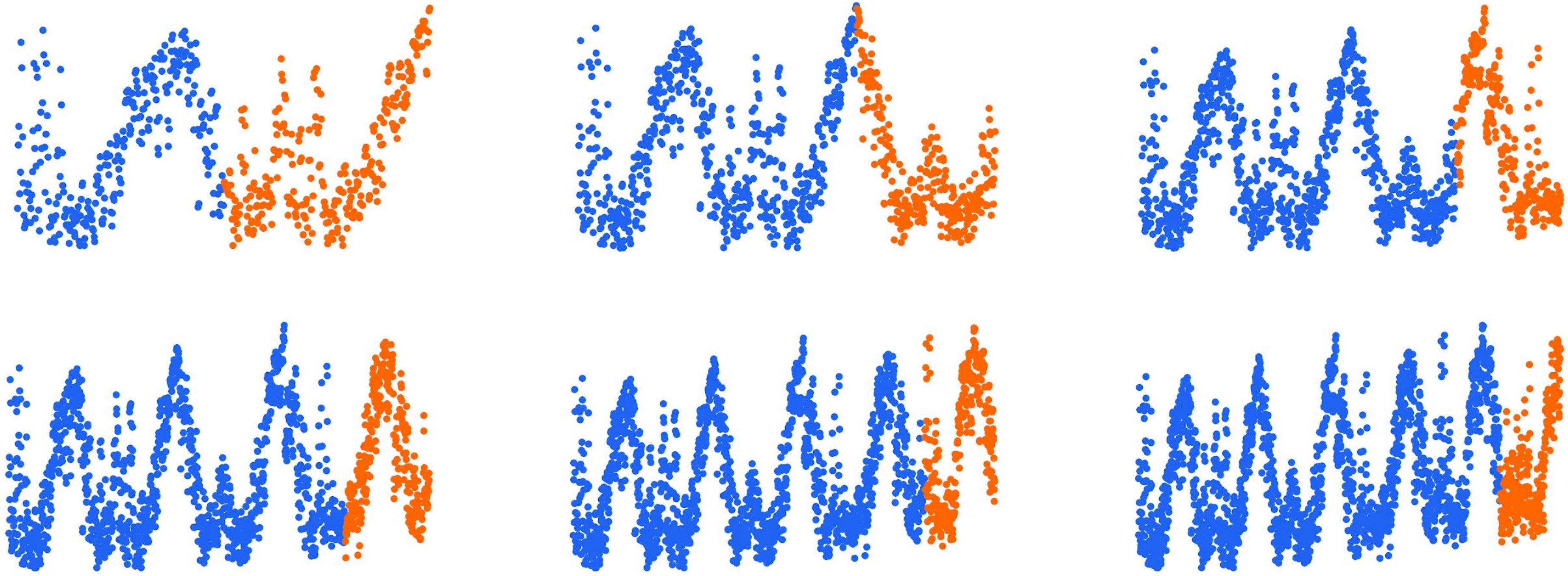
For time series data, random train/test splits leak information



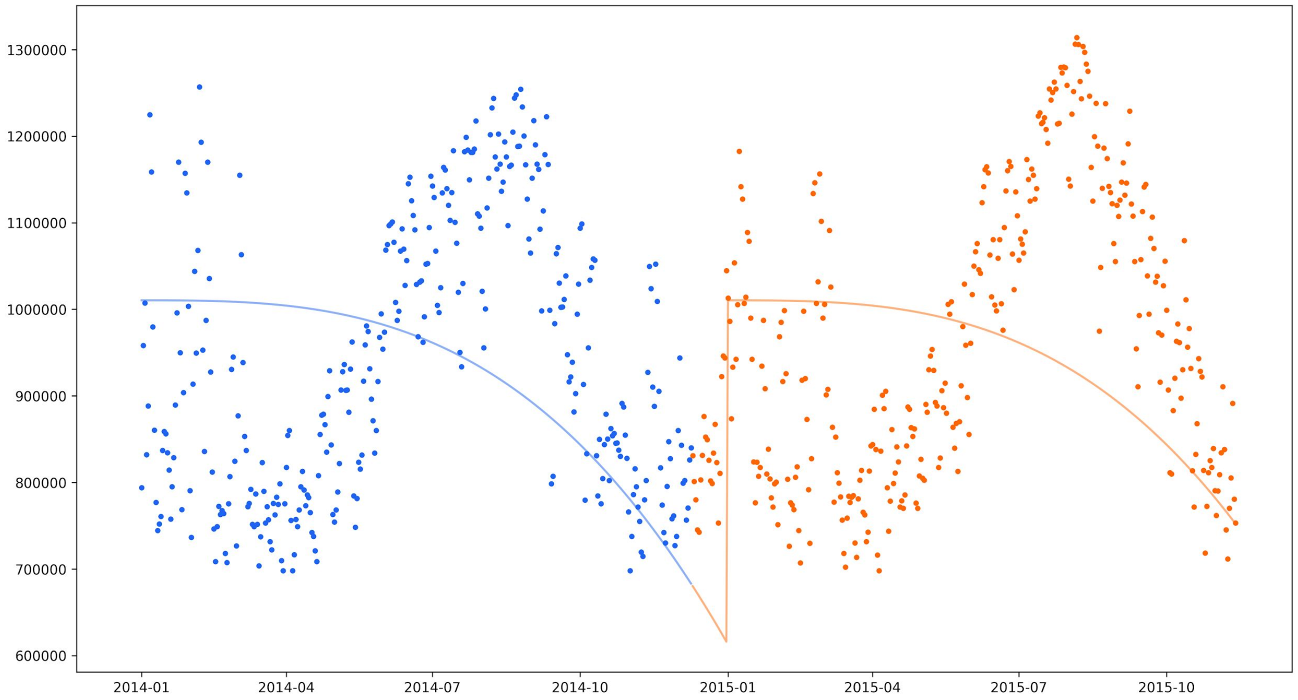
For time series data, random train/test splits leak information



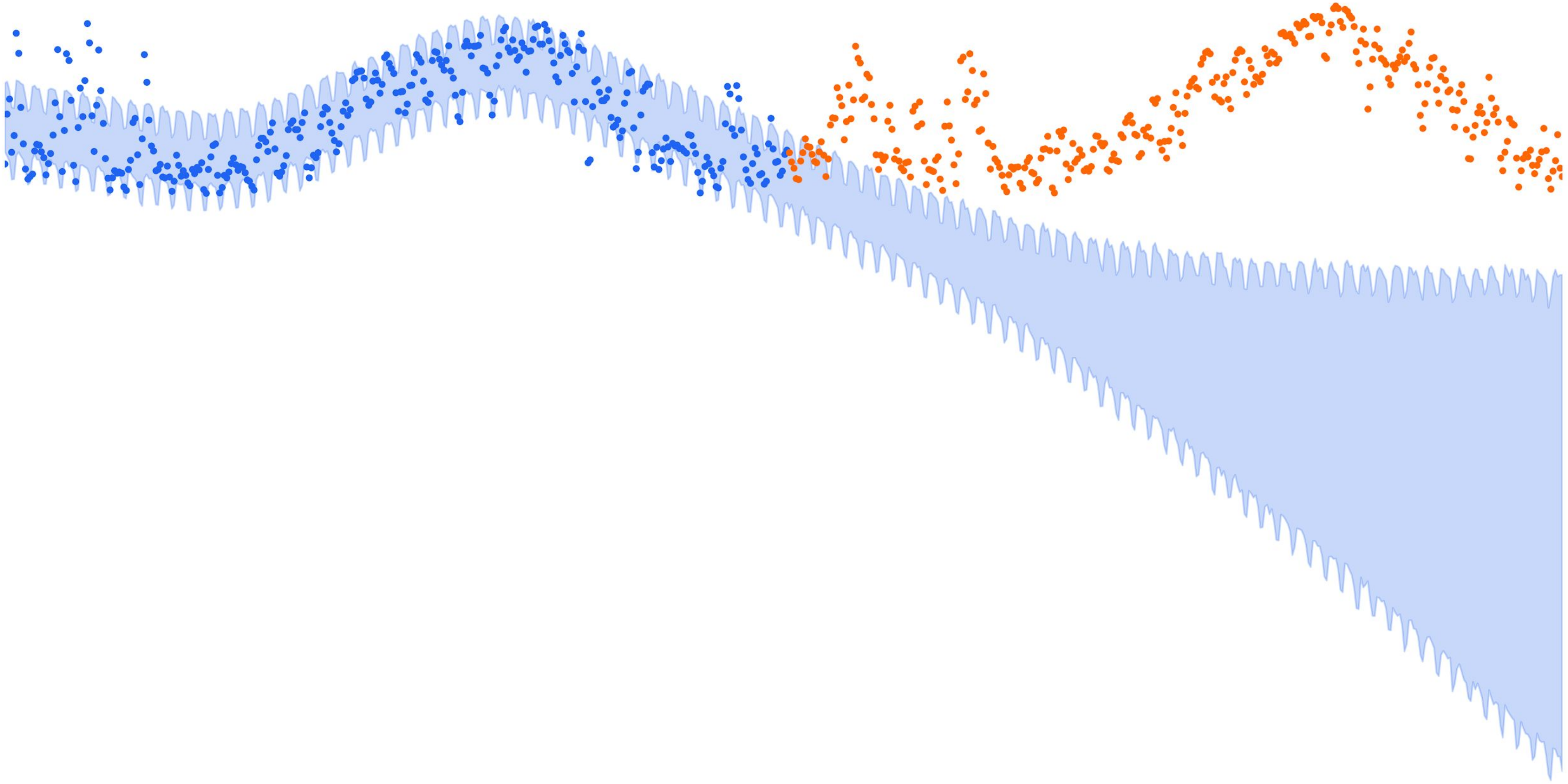
When using time series data, split based on time

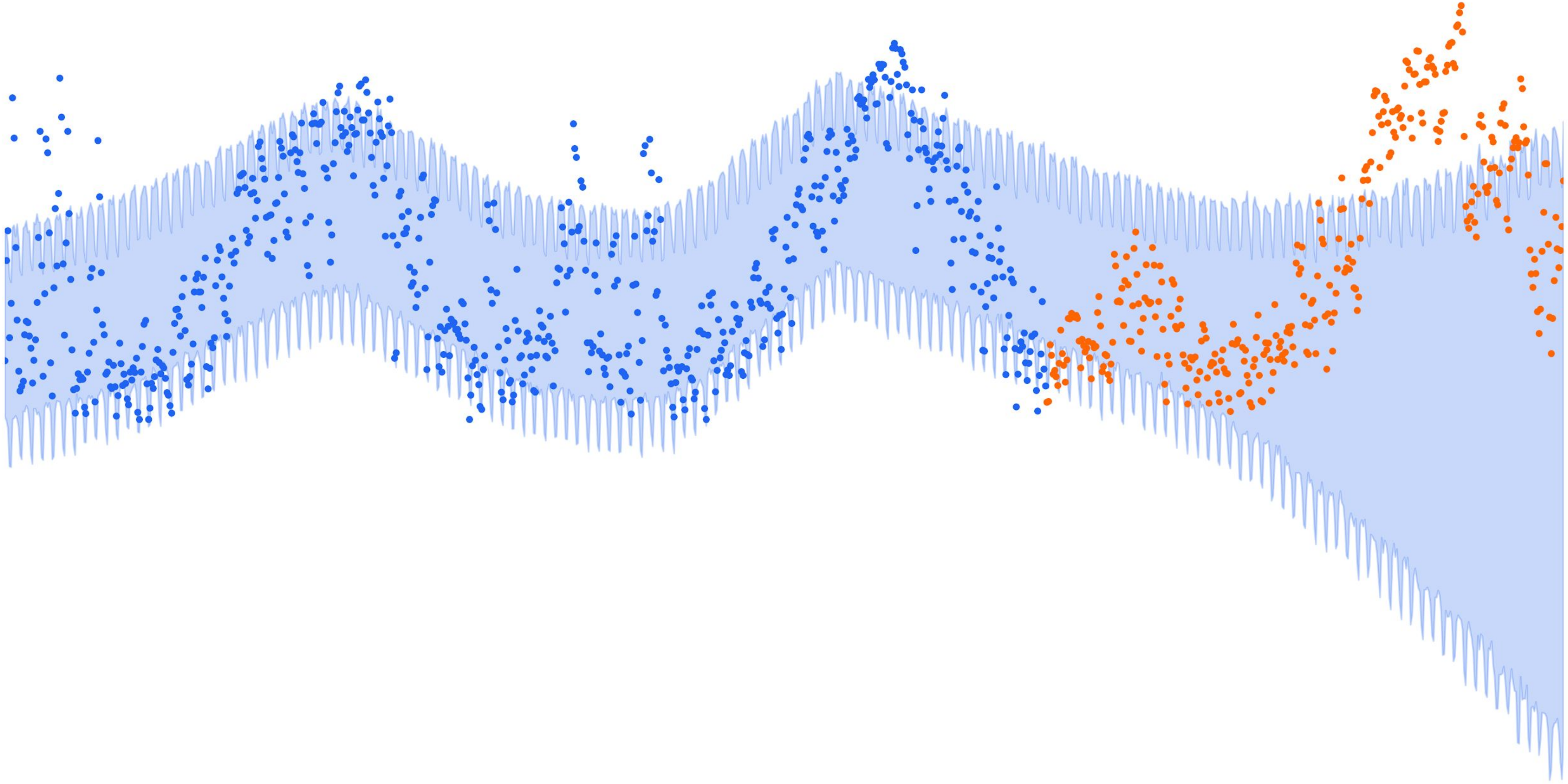


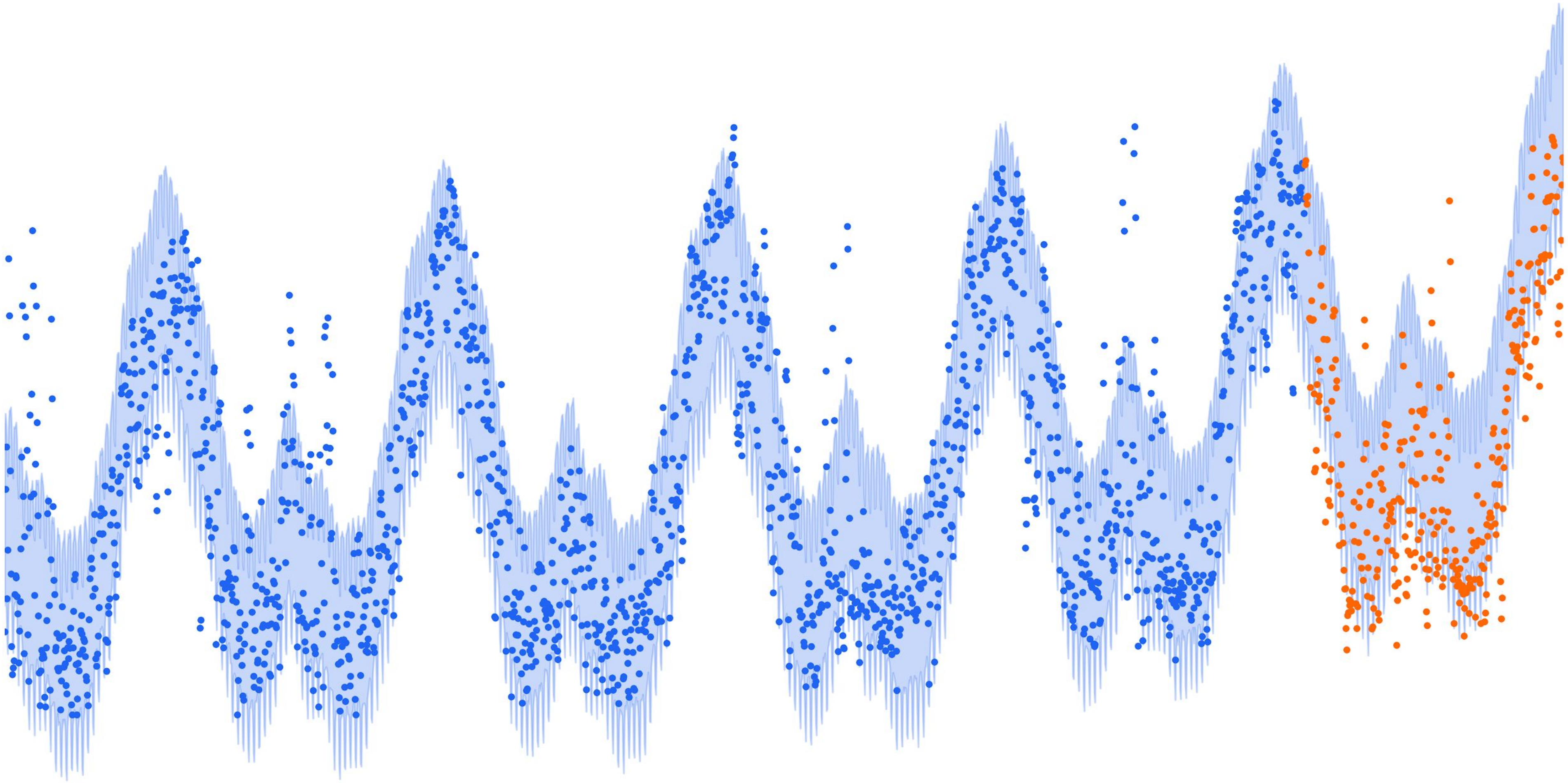
Some models learn poorly from time series data



https://facebook.github.io/prophet/







UC2: LESSONS LEARNED

- Time series data is special
- Seasonality
- Train/test split – Don’t use random!

Agenda

Machine learning intro

UC0: Credit card applications

UC1: Teach a computer ASL

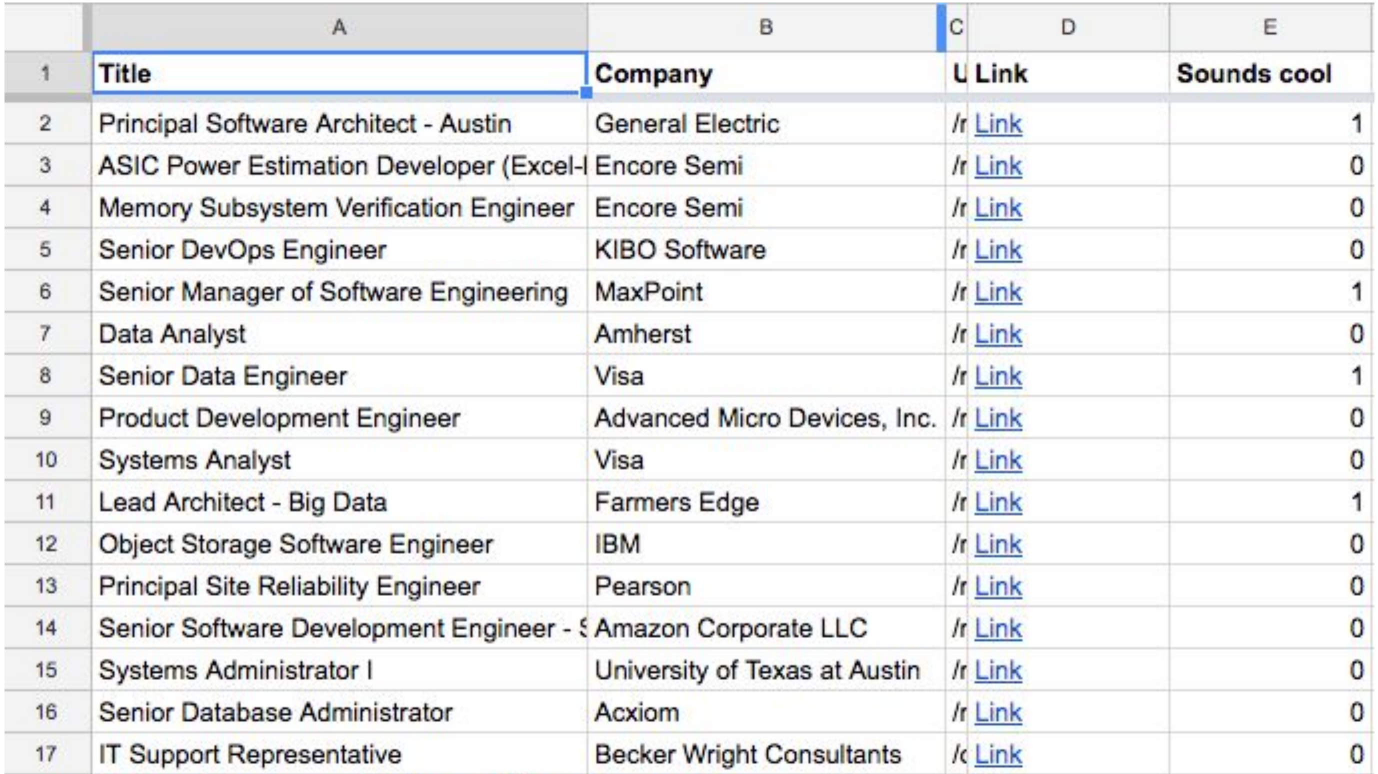
UC2: Forecasting energy load

UC3: Use ML to find your next job

➔ What’s the problem?

Passive job hunting

➔ What does the data look like?

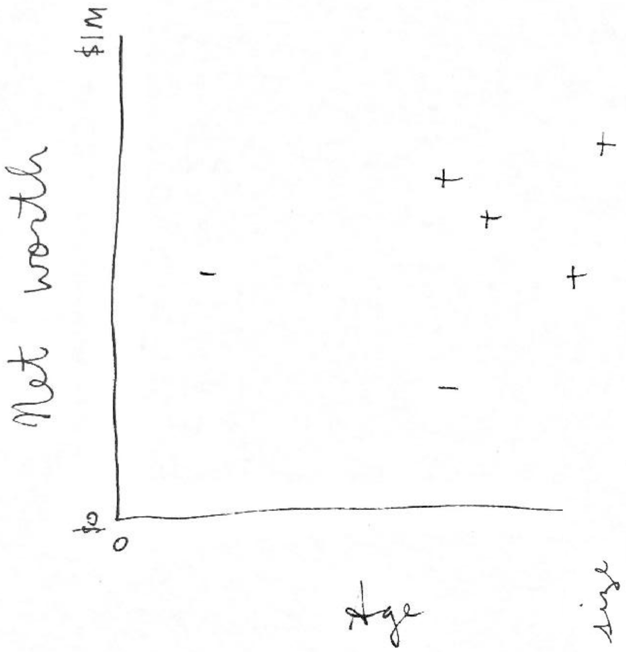


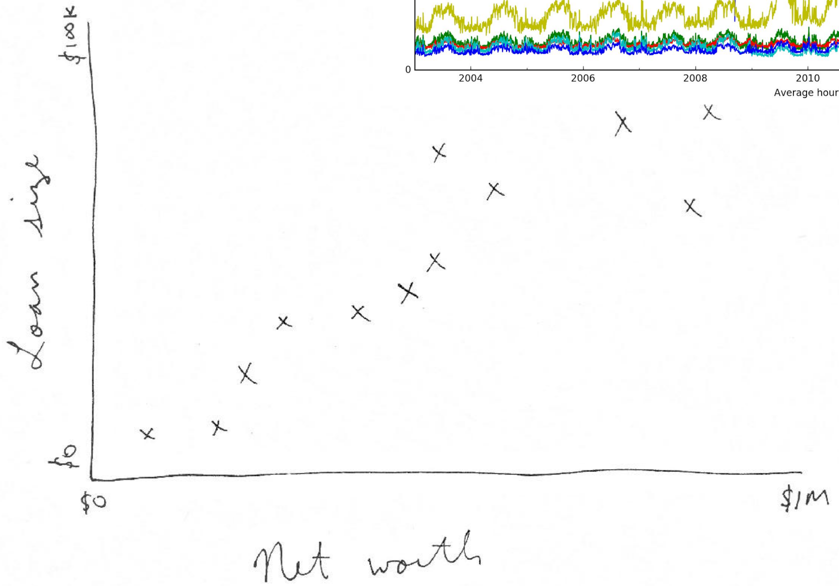
	A	B	C	D	E
1	**Title**	**Company**	**U**	**Link**	**Sounds cool**
2	Principal Software Architect - Austin	General Electric	/r	Link	1
3	ASIC Power Estimation Developer (Excel-I	Encore Semi	/r	Link	0
4	Memory Subsystem Verification Engineer	Encore Semi	/r	Link	0
5	Senior DevOps Engineer	KIBO Software	/r	Link	0
6	Senior Manager of Software Engineering	MaxPoint	/r	Link	1
7	Data Analyst	Amherst	/r	Link	0
8	Senior Data Engineer	Visa	/r	Link	1
9	Product Development Engineer	Advanced Micro Devices, Inc.	/r	Link	0
10	Systems Analyst	Visa	/r	Link	0
11	Lead Architect - Big Data	Farmers Edge	/r	Link	1
12	Object Storage Software Engineer	IBM	/r	Link	0
13	Principal Site Reliability Engineer	Pearson	/r	Link	0
14	Senior Software Development Engineer - S	Amazon Corporate LLC	/r	Link	0
15	Systems Administrator I	University of Texas at Austin	/r	Link	0
16	Senior Database Administrator	Acxiom	/r	Link	0
17	IT Support Representative	Becker Wright Consultants	/c	Link	0

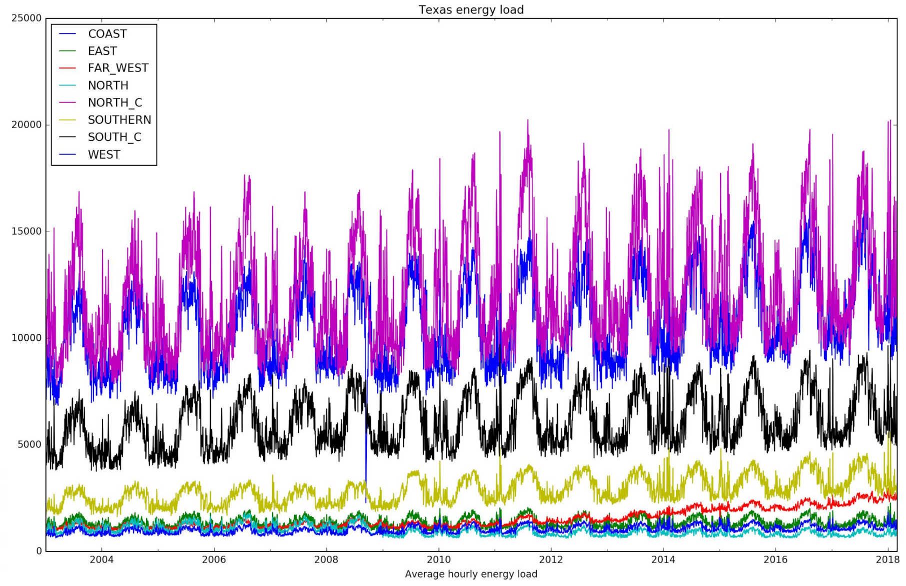
- **What kind of ML problem is this?**

➔ What kind of ML problem is this?

Classification


$1M
Net worth
$0
0
Age


$100K
Loan size
$0
$0
$1M
Net worth


Texas energy load
COAST
EAST
FAR_WEST
NORTH
NORTH_C
SOUTHERN
SOUTH_C
WEST
25000
20000
15000
10000
5000
0
2004
2006
2008
2010
2012
2014
2016
2018
Average hourly energy load

(Data Scientist, sounds_cool=True) $\longrightarrow$ **(5, 1)**

???

	Engi-neer	web	Applica-tions	sr	jr	analytics	software	data	developer
Sr. Web Applications Developer - Data Analytics	0	1	1	1	0	1	0	1	1
Jr. Software Developer	0	0	0	0	1	0	1	0	1
Sr. Data Engineer	1	0	0	1	0	0	0	1	0
Data data data data	0	0	0	0	0	0	0	4	0

(Data Scientist, sounds_cool=True)

⬇

(1, 0, 0, 1, 0, 0, 0, 0, 0, 1)

```
X = rated_jobs['title'].as_matrix()
y = rated_jobs['sounds_cool'].as_matrix()

vect = CountVectorizer()
Xp = vect.fit_transform(X).toarray()
clf = LogisticRegression().fit(Xp, y)

new_job_ratings = clf.predict(new_jobs)

# array([ 0.,  0.,  0.,  1.,  0.,  0.,  0.,  1.])
```

```python
X = rated_jobs['title'].as_matrix()
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# array([ 0.,  0.,  0.,  1.,  0.,  0.,  0.,  1.])
```

Accuracy

Classification error: 0.197

(awesome!)

Accuracy

Classification error: 0.197

(awesome!)

But wait…

Accuracy

Classification error: 0.197

(awesome!)

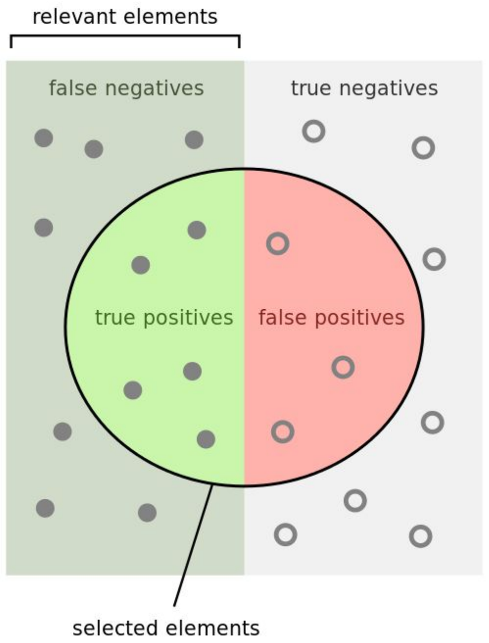
But wait…

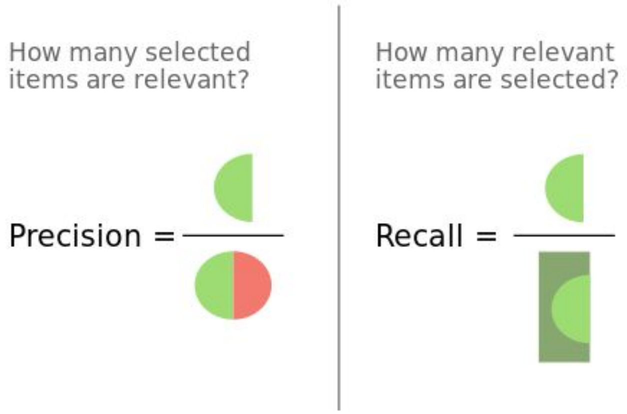
Base rate == 0.197

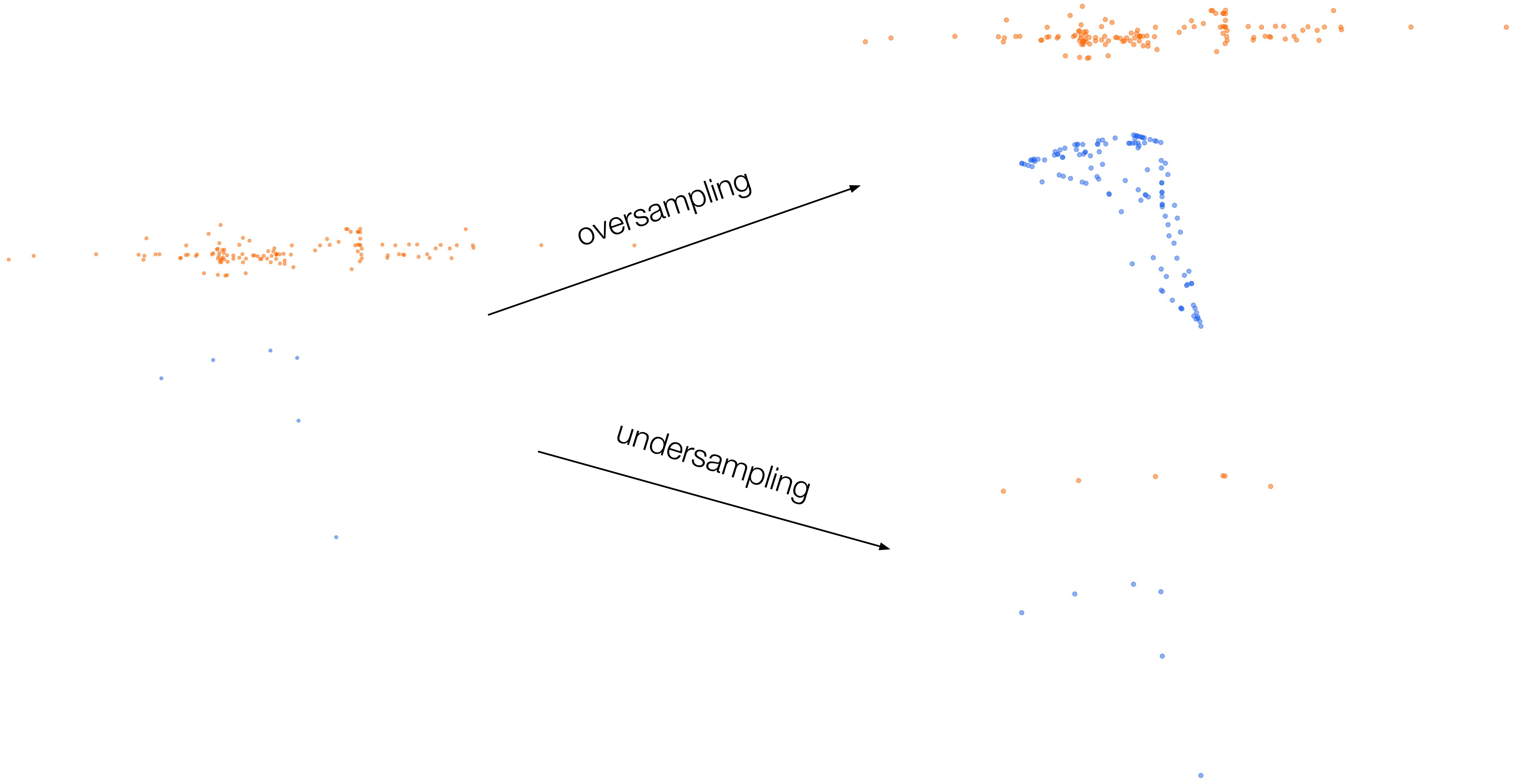
	Actual 0	Actual 1	Total
Predicted 0	400	100	500
Predicted 1	0	0	0
Total	400	100	

Imbalance

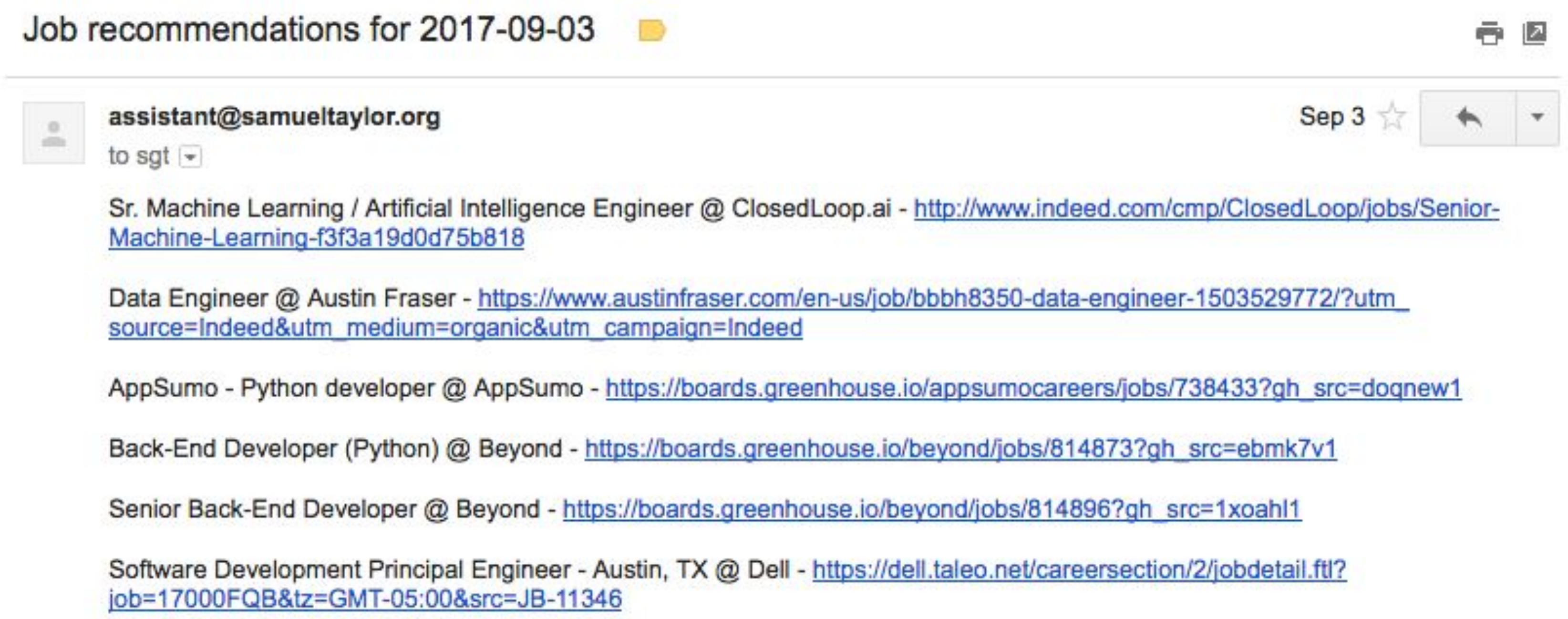
Better error metrics




How many selected items are relevant?
Precision =
How many relevant items are selected?
Recall =


oversampling
undersampling

End result



Job recommendations for 2017-09-03

assistant@samueltaylor.org
to sgt

Sep 3

Sr. Machine Learning / Artificial Intelligence Engineer @ ClosedLoop.ai - http://www.indeed.com/cmp/ClosedLoop/jobs/Senior-Machine-Learning-f3f3a19d0d75b818

Data Engineer @ Austin Fraser - https://www.austinfraser.com/en-us/job/bbbh8350-data-engineer-1503529772/?utm_source=Indeed&utm_medium=organic&utm_campaign=Indeed

AppSumo - Python developer @ AppSumo - https://boards.greenhouse.io/appsumocareers/jobs/738433?gh_src=doqnew1

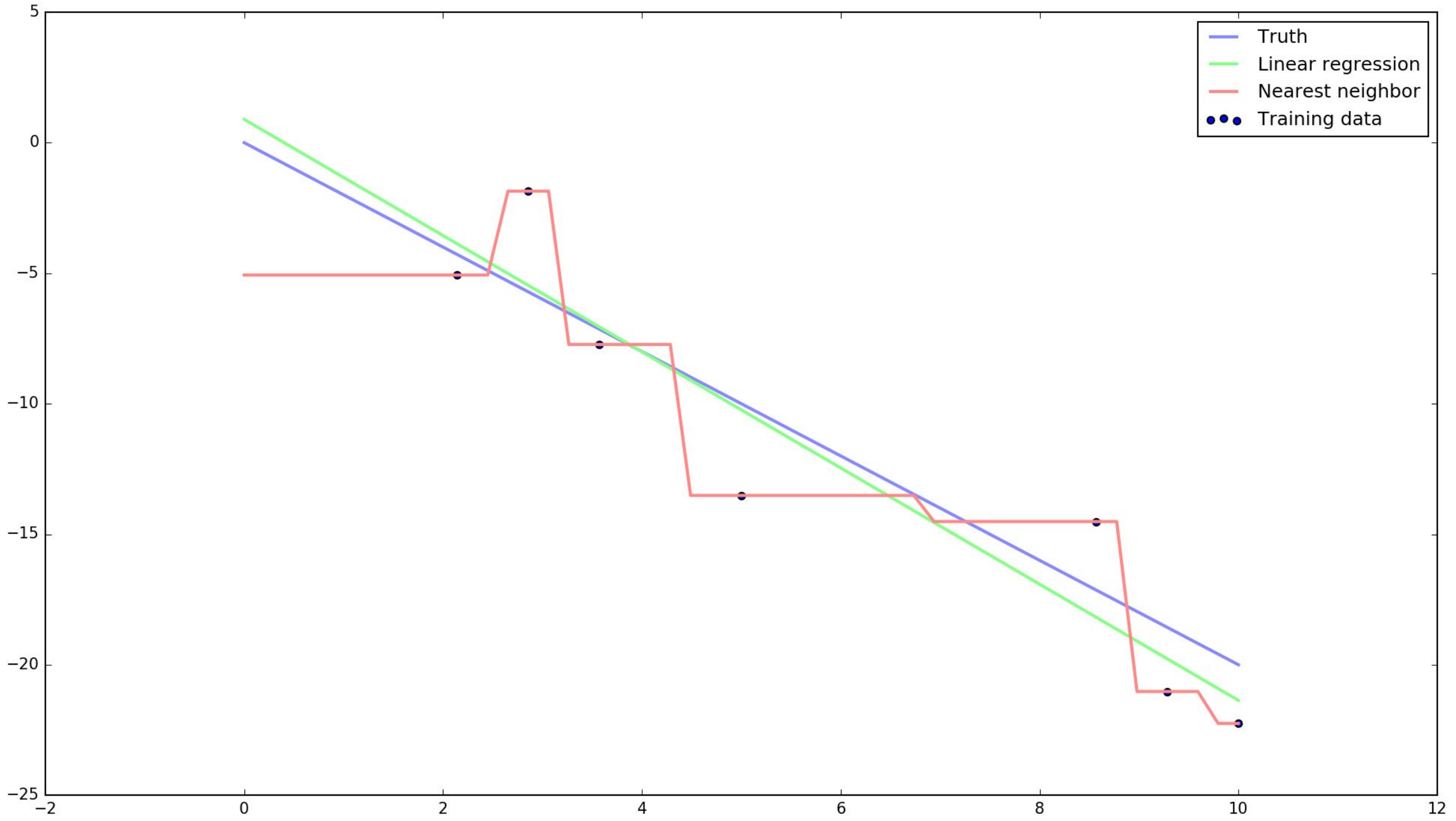
Back-End Developer (Python) @ Beyond - https://boards.greenhouse.io/beyond/jobs/814873?gh_src=ebmk7v1

Senior Back-End Developer @ Beyond - https://boards.greenhouse.io/beyond/jobs/814896?gh_src=1xoahl1

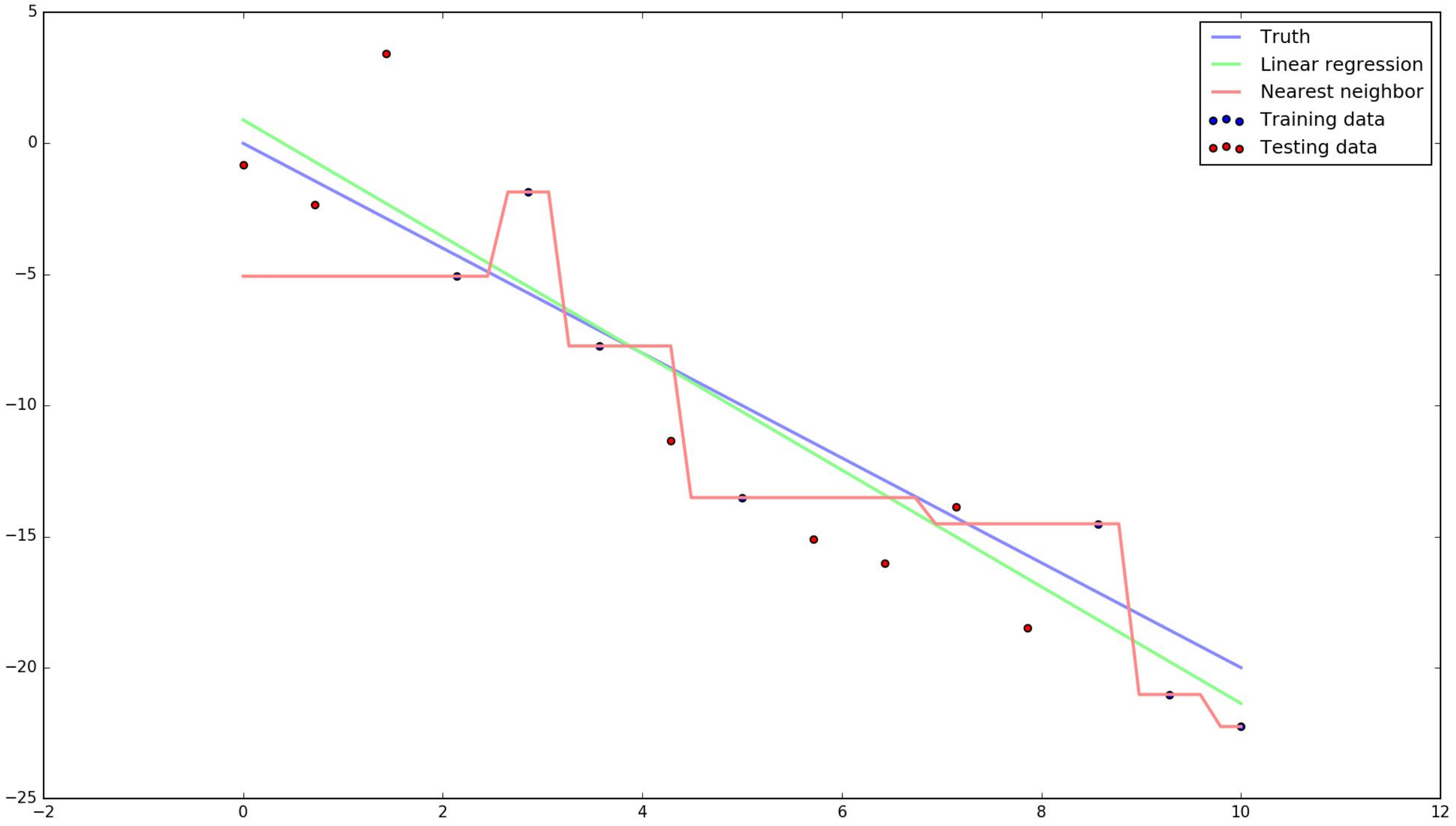
Software Development Principal Engineer - Austin, TX @ Dell - https://dell.taleo.net/careersection/2/jobdetail.ftl?job=17000FQB&tz=GMT-05:00&src=JB-11346

UC3: LESSONS LEARNED

- Understand the base rate
- Simple doesn’t mean ineffective
- Approximation-generalization tradeoff



5
0
−5
−10
−15
−20
−25
−2
0
2
4
6
8
10
12
Truth
Linear regression
Nearest neighbor
Training data


Truth
Linear regression
Nearest neighbor
Training data
Testing data
5
0
−5
−10
−15
−20
−25
−2
0
2
4
6
8
10
12

UC3: LESSONS LEARNED

- Understand the base rate
- Simple doesn't mean ineffective
- Approximation / generalization tradeoff

also, it's easier

Deep breath, everyone

Takeaways

→ **Supervised learning**

Using past examples to predict a continuous or discrete value

Takeaways

➔ **Supervised learning**

Using past examples to predict a continuous or discrete value

➔ **Measuring performance**

Split data into training and testing subsets

Takeaways

→ **Supervised learning**

Using past examples to predict a continuous or discrete value

→ **Measuring performance**

Split data into training and testing subsets

→ **K.I.S.S.**

Try the simplest thing that could possibly work

Takeaways

- ➔ **Supervised learning**

  Using past examples to predict a continuous or discrete value

- ➔ **Measuring performance**

  Split data into training and testing subsets

- ➔ **K.I.S.S.**

  Try the simplest thing that could possibly work

- ➔ **Test and iterate**

indeed

slides: **go.indeed.com/SamuelATO**
twitter: **@SamuelDataT**
email: **sgt@samueltaylor.org**