Machine Learning Crash Course

Samuel Taylor


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Master

Ryan Born

Machine Learning Crash Course

Samuel Taylor

This talk **is**

- An introduction to machine learning
- Friendly to newcomers
- Helpful to experienced people *(I hope)*
- Oriented toward application
- Respectful of theory

This talk **is not**

This talk is

- An introduction to machine learning
- Friendly to newcomers
- Helpful to experienced people
- Oriented toward application
- Respectful of theory

This talk is not

- Going to turn you into a data scientist
- The end-all, be-all, entirely comprehensive reference on statistics, artificial intelligence, big data, and machine learning
- A detailed tutorial or guide to implementation

Agenda

- Introduction to machine learning
- Use case 0: credit card applications (practice)
- Use case 1: teach a computer sign language
- Use case 2: forecast energy usage in Texas
- Use case 3: use machine learning to find your next job
- Wrap up

Machine learning?

Supervised

- Classification
- Regression

Unsupervised

- Clustering

Other stuff

- Reinforcement

Supervised

- Classification
- Regression

Unsupervised

- Clustering

Other stuff

- Reinforcement

Supervised

- Classification
- Regression

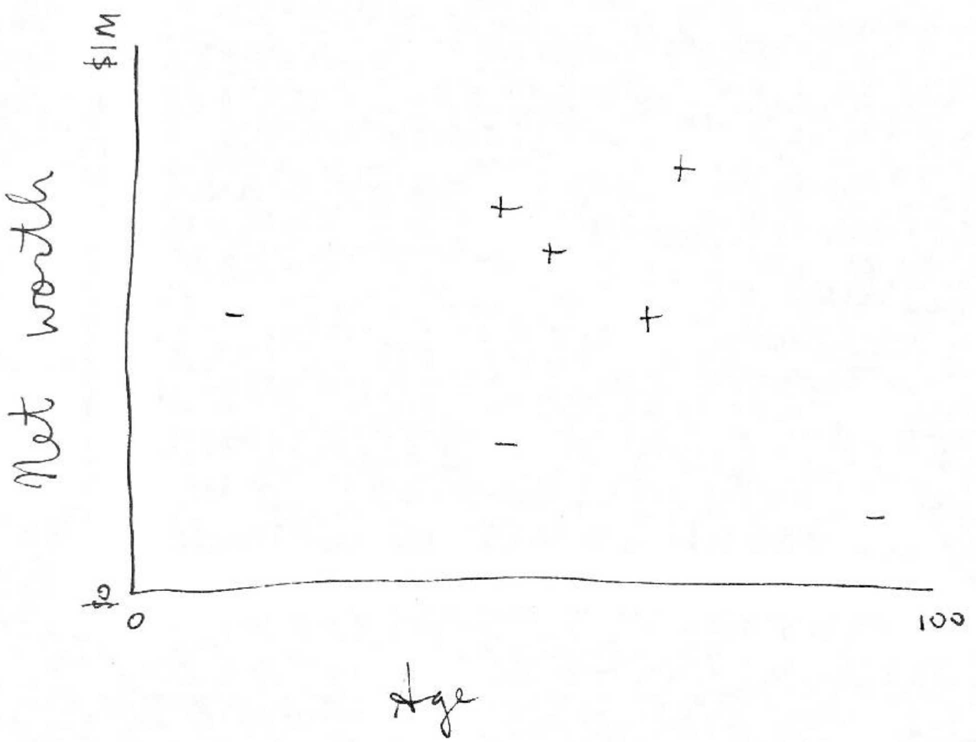
Unsupervised

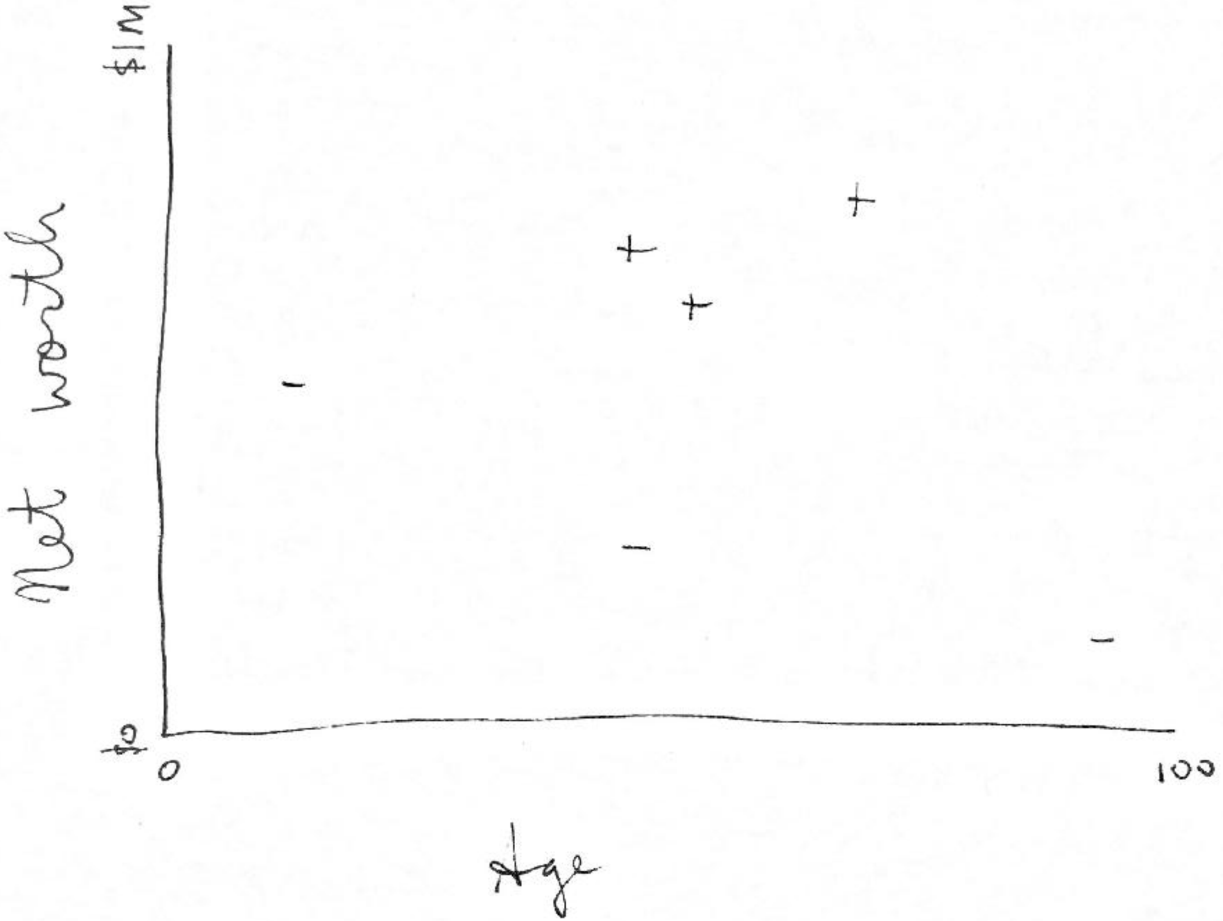
- Clustering

Other stuff

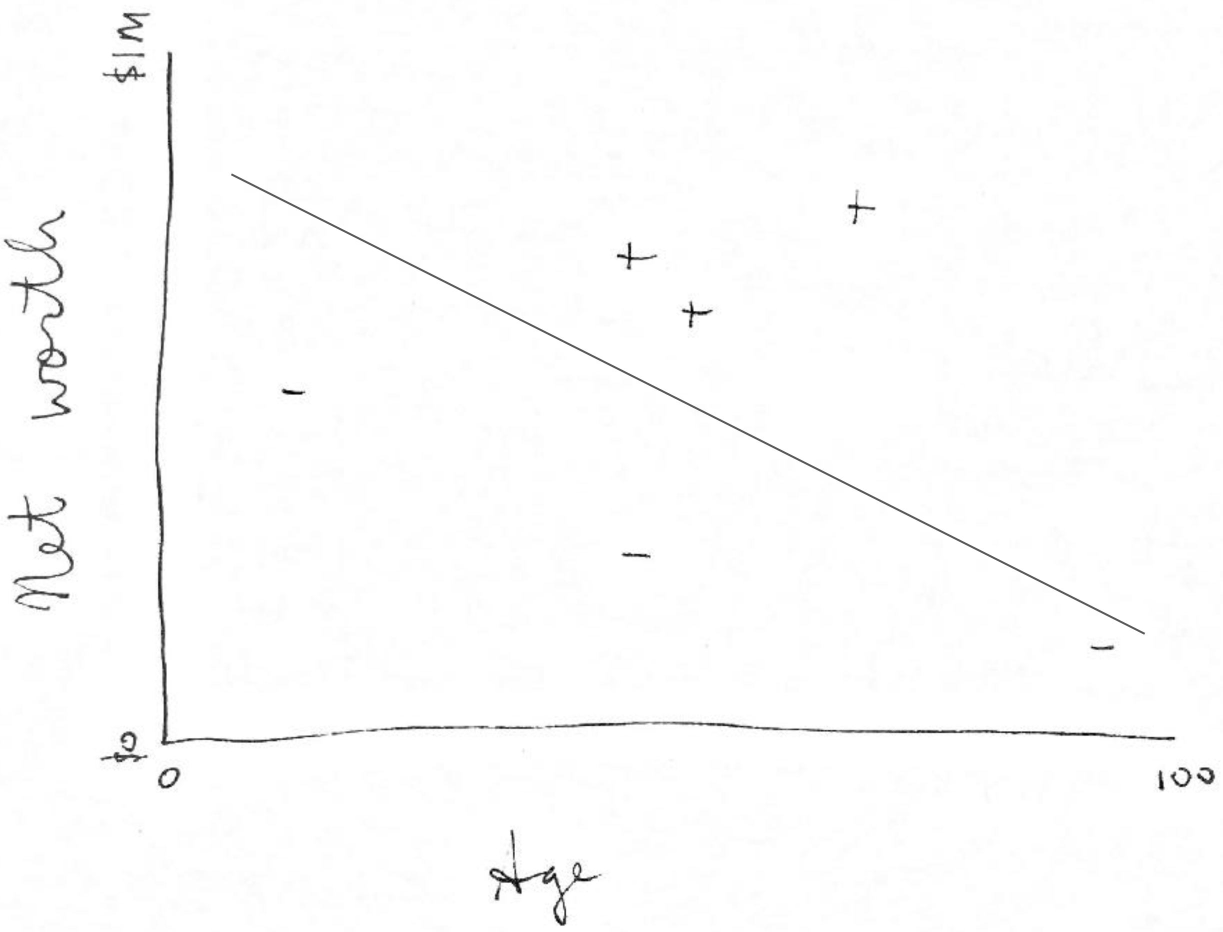
- Reinforcement

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

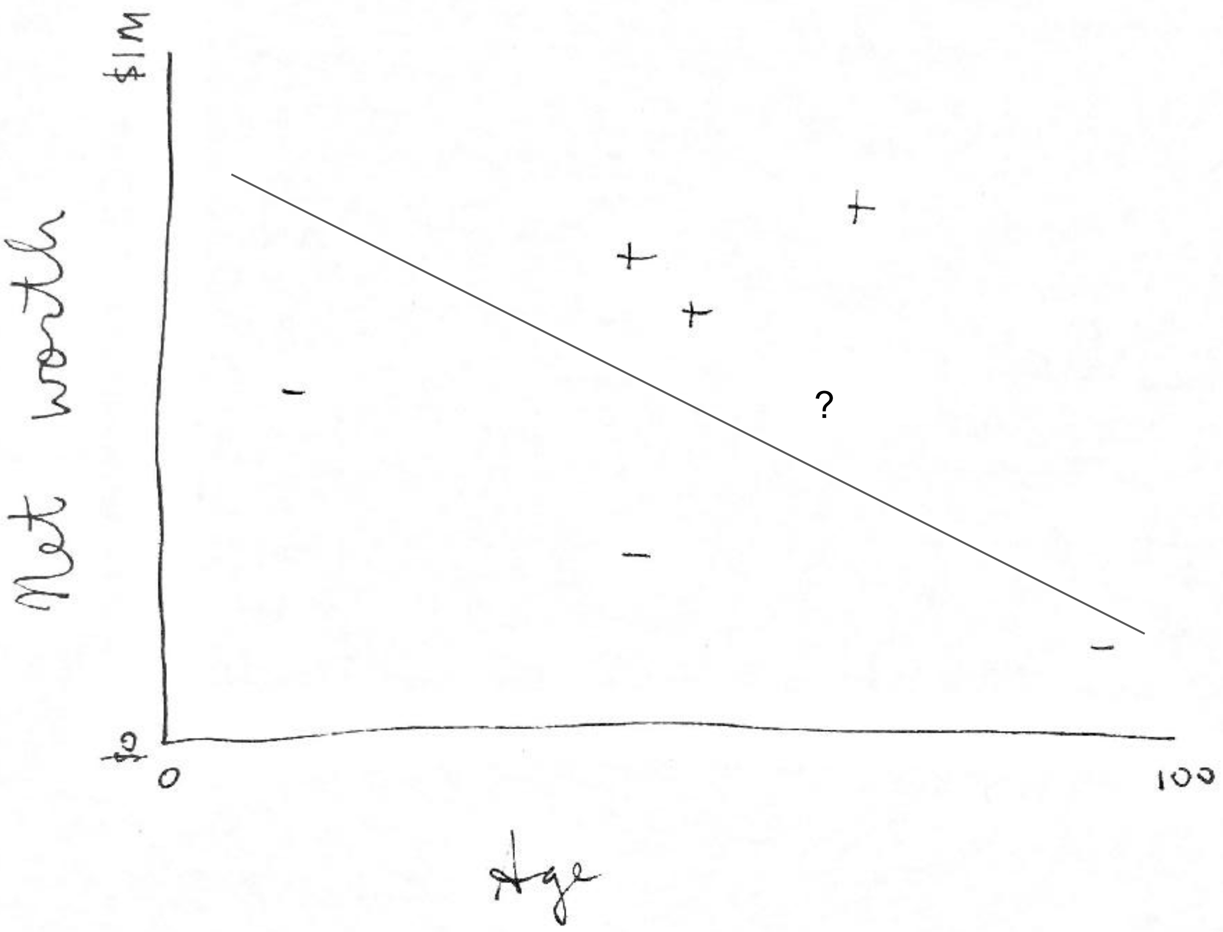


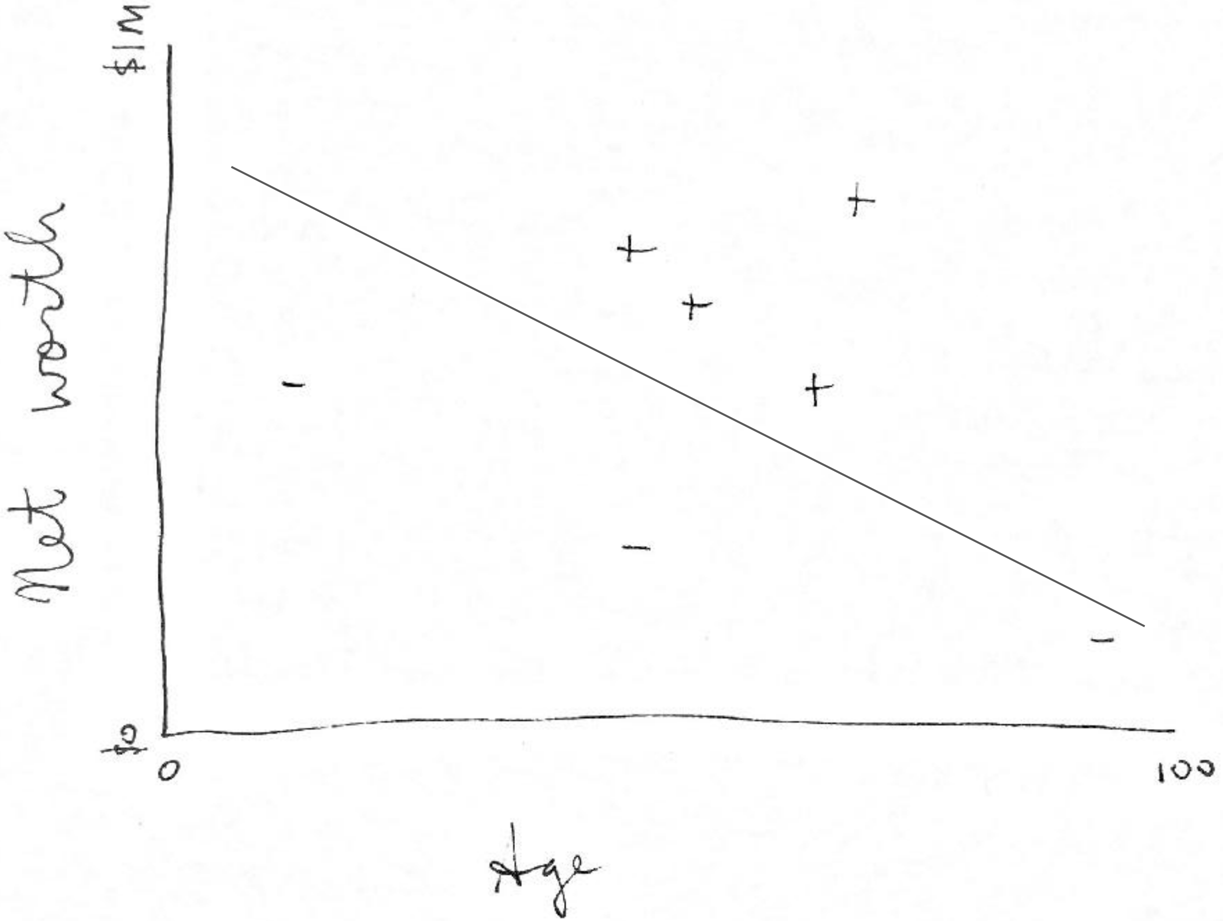


$1M
Net worth
$0
0
100
Age

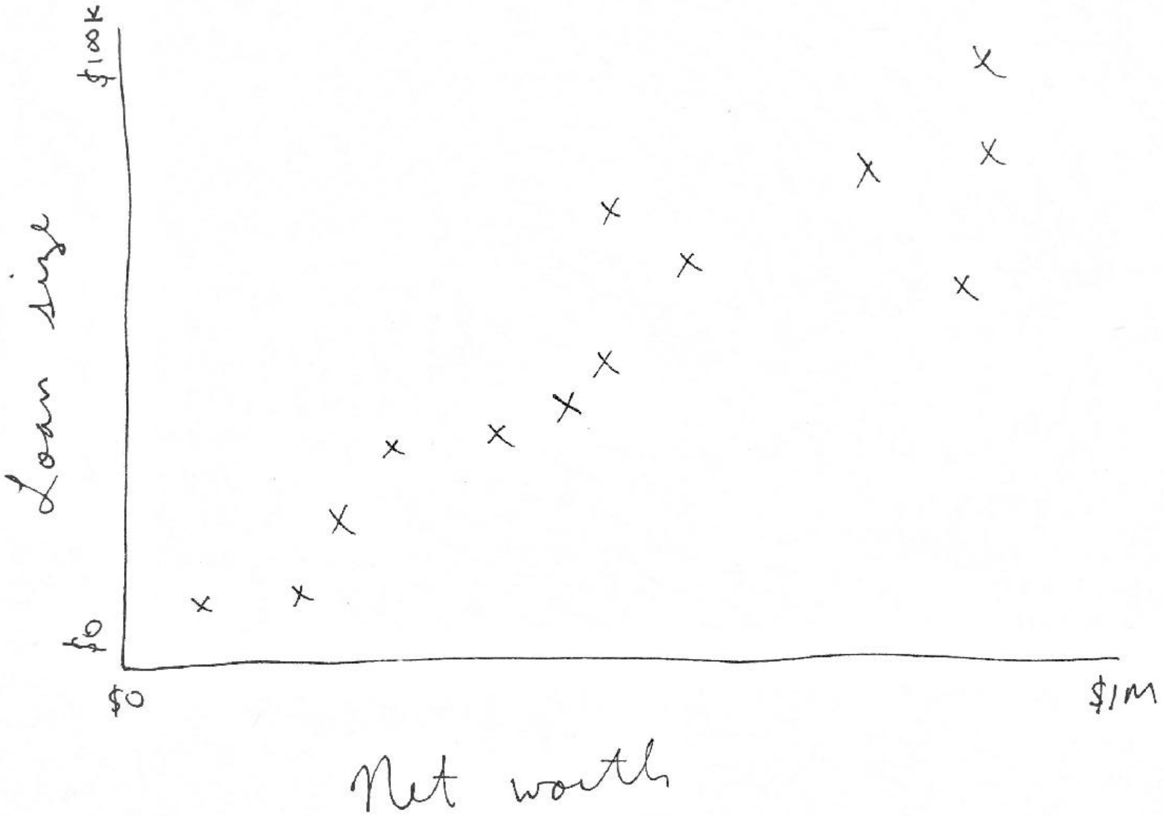


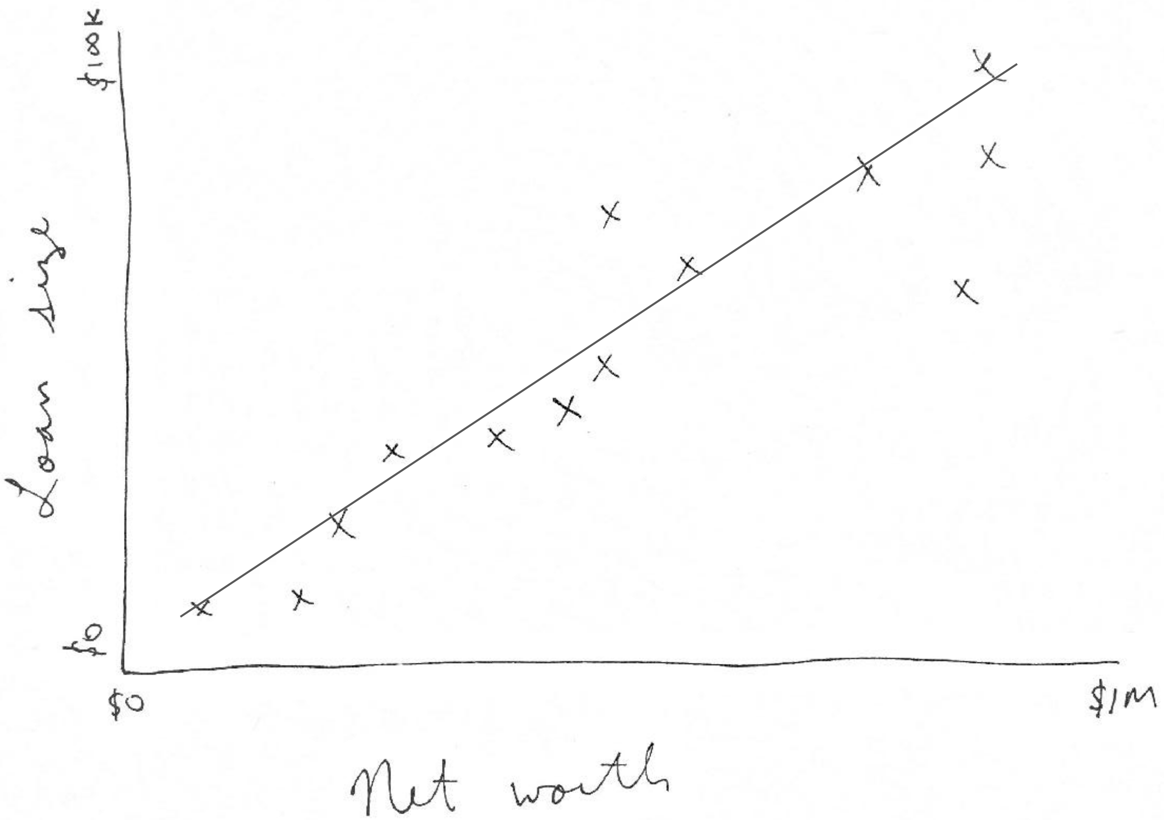
$1M
Net worth
$0
0
100
Age

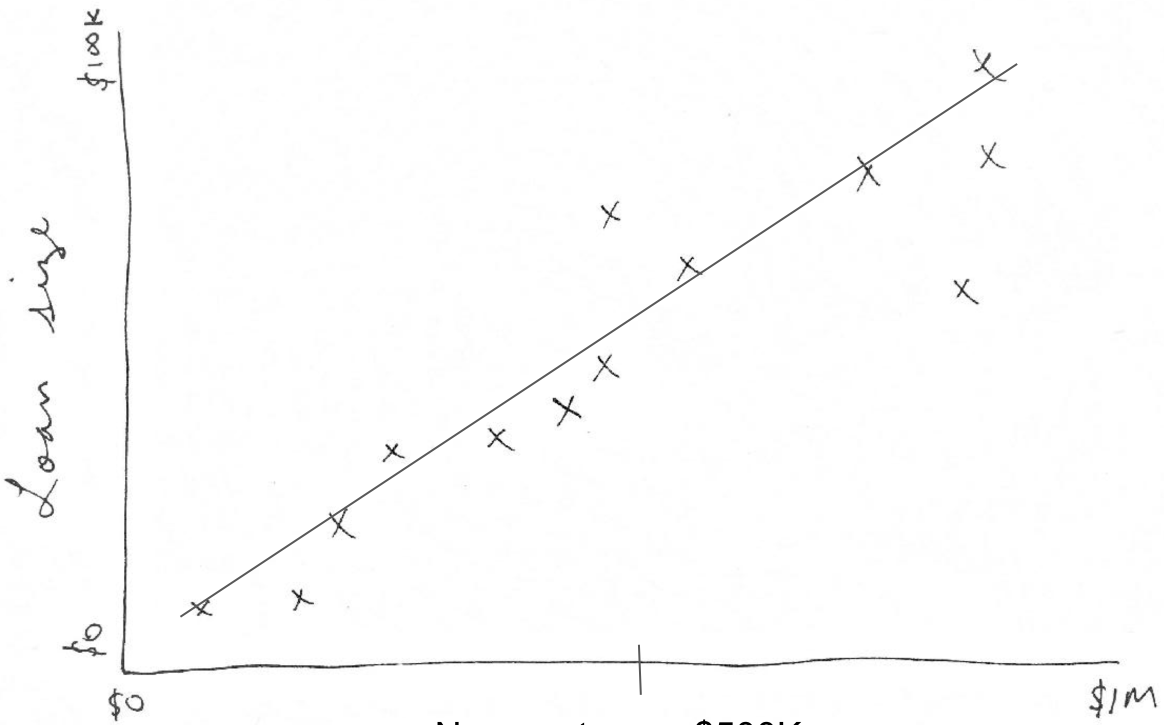

$1M
Net worth
?
$0
0
100
Age


$1M
Net worth
$0
0
100
Age

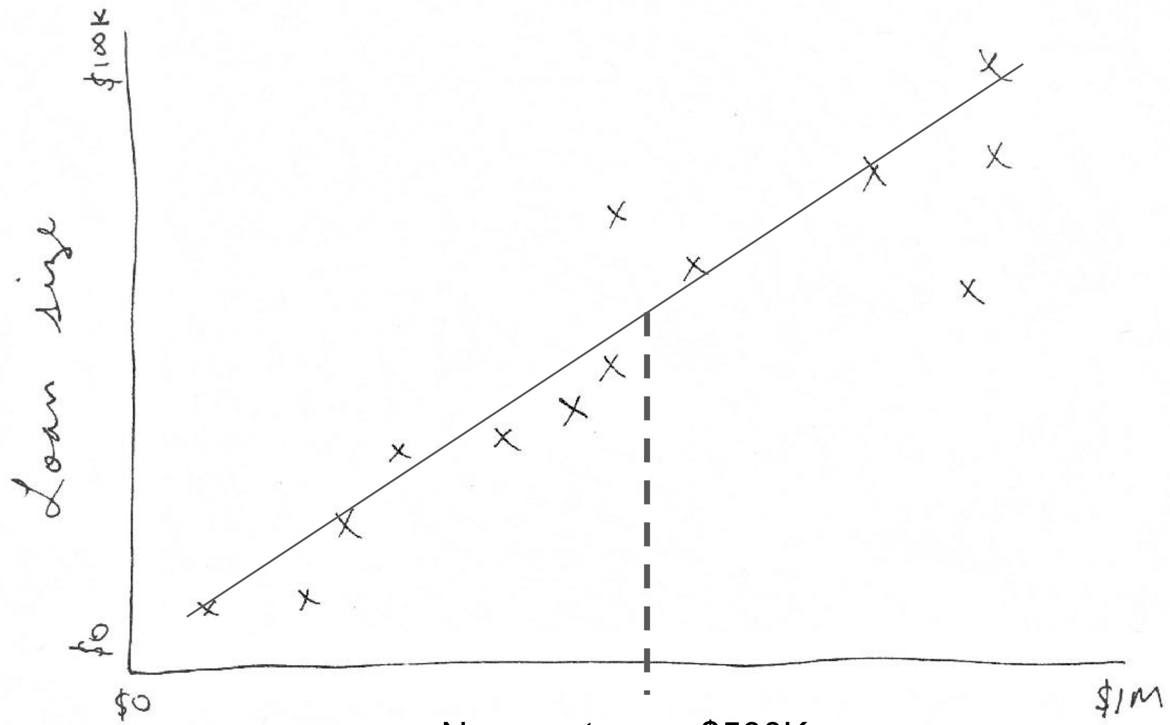
Regression


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

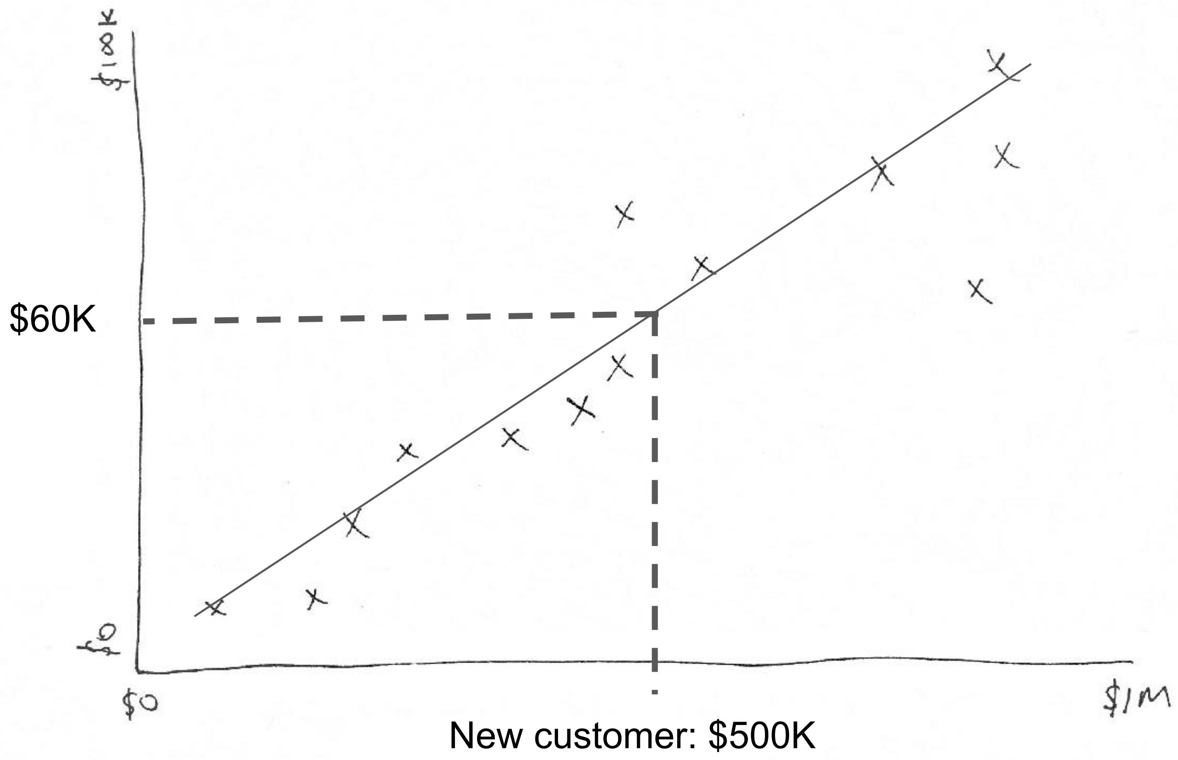

$100K
$0
Loan size
$0
$1M
Net worth



New customer: $500K



New customer: $500K


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

Supervised

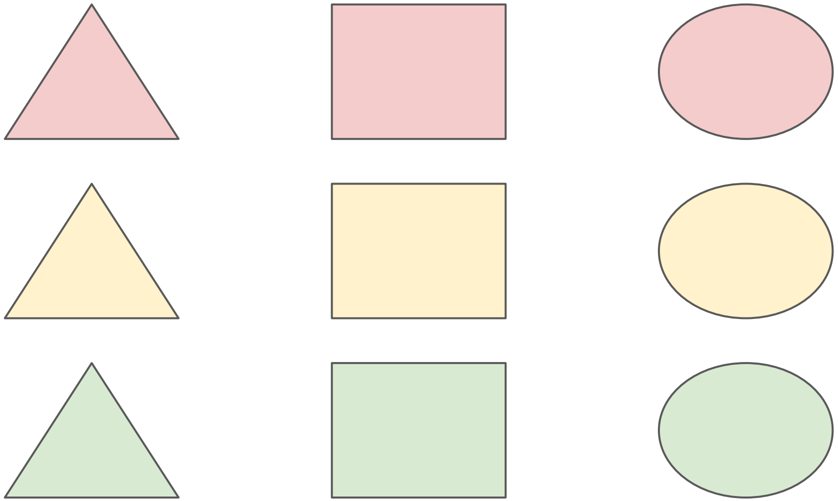
- Regression
- Classification

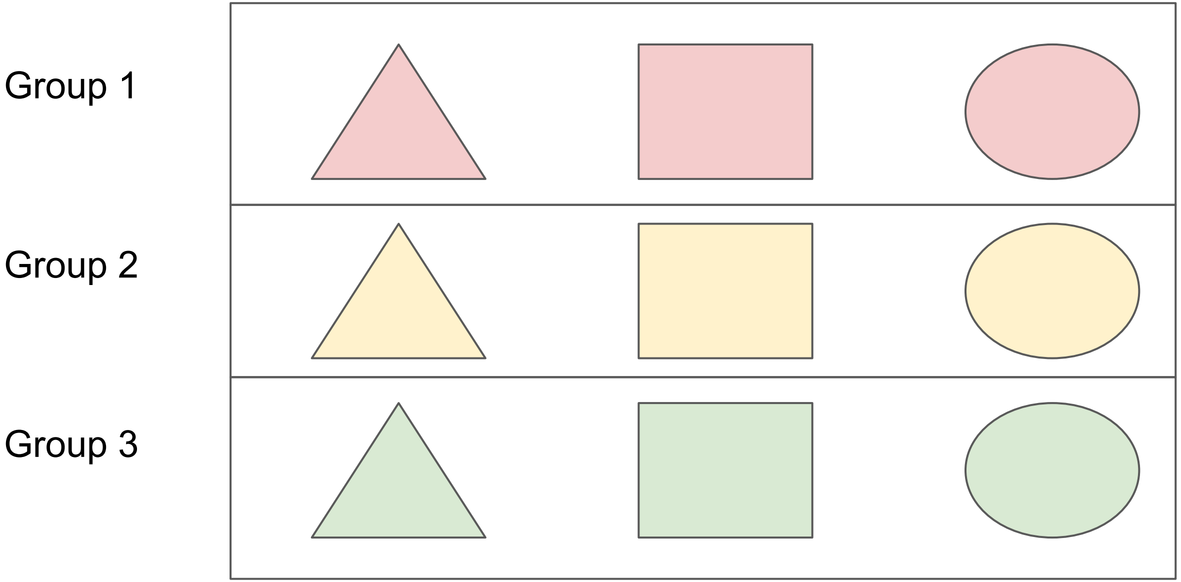
Unsupervised

- Clustering

Other stuff

- Reinforcement




Group 1
Group 2
Group 3

Supervised

- Regression
- Classification

Unsupervised

- Clustering

Other stuff

- Reinforcement

Machine learning

- Goal: Find *f(x)*
- Problem: *f(x)* is unknown
- But: we can measure some points from *f(x)*
- Algorithms to find a *g(x)* that approximates *f(x)*

UC0: Handle an application for a credit card

UC0: Credit card application

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

UC0: Credit card application

- What's the problem?
  - Should we (the bank) give this consumer a credit card?
- What does the data look like?
- What kind of ML problem is this?
- Solution
- Lessons learned

UC0: Credit card application

- What's the problem?
- What does the data look like?
- What kind of ML problem is this?
- Solution
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Age	Net worth	Given credit?
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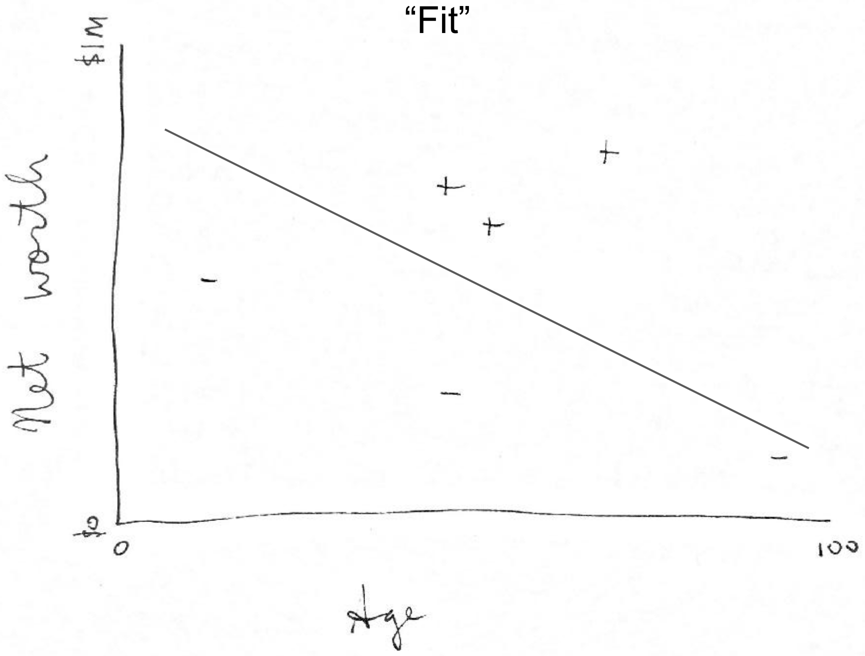
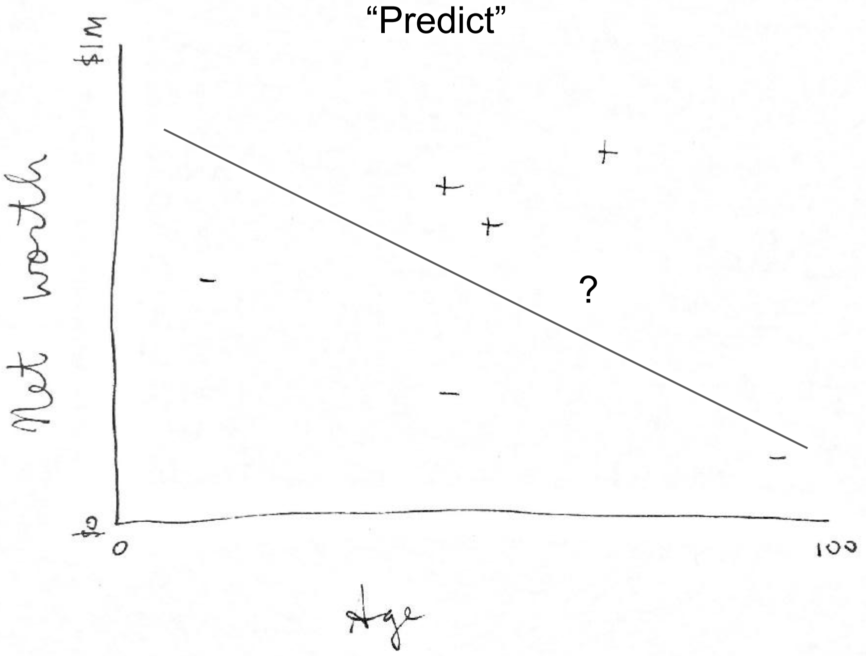
UC0: Credit card application

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

UC0: Solution

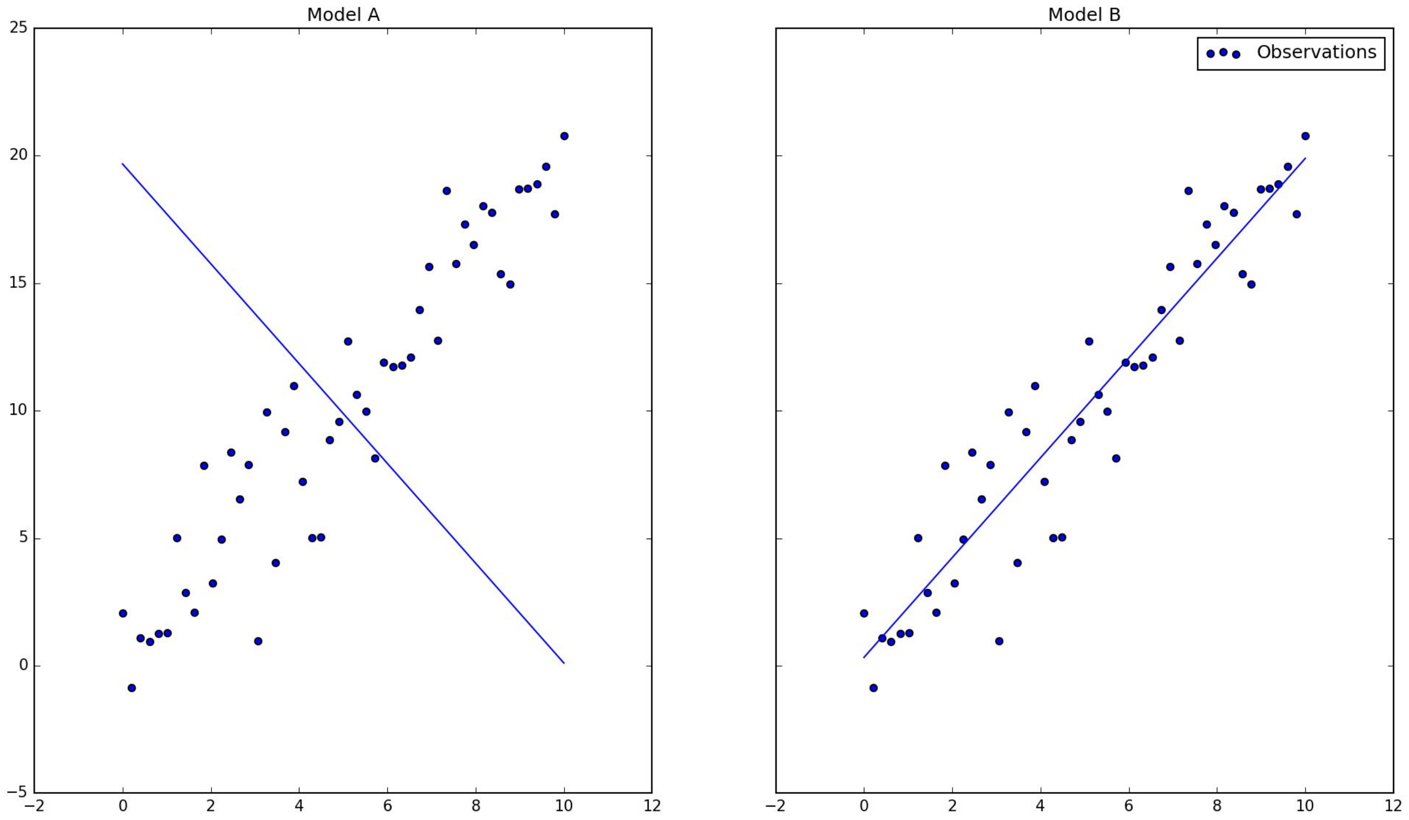
- LinearSVC (sklearn)



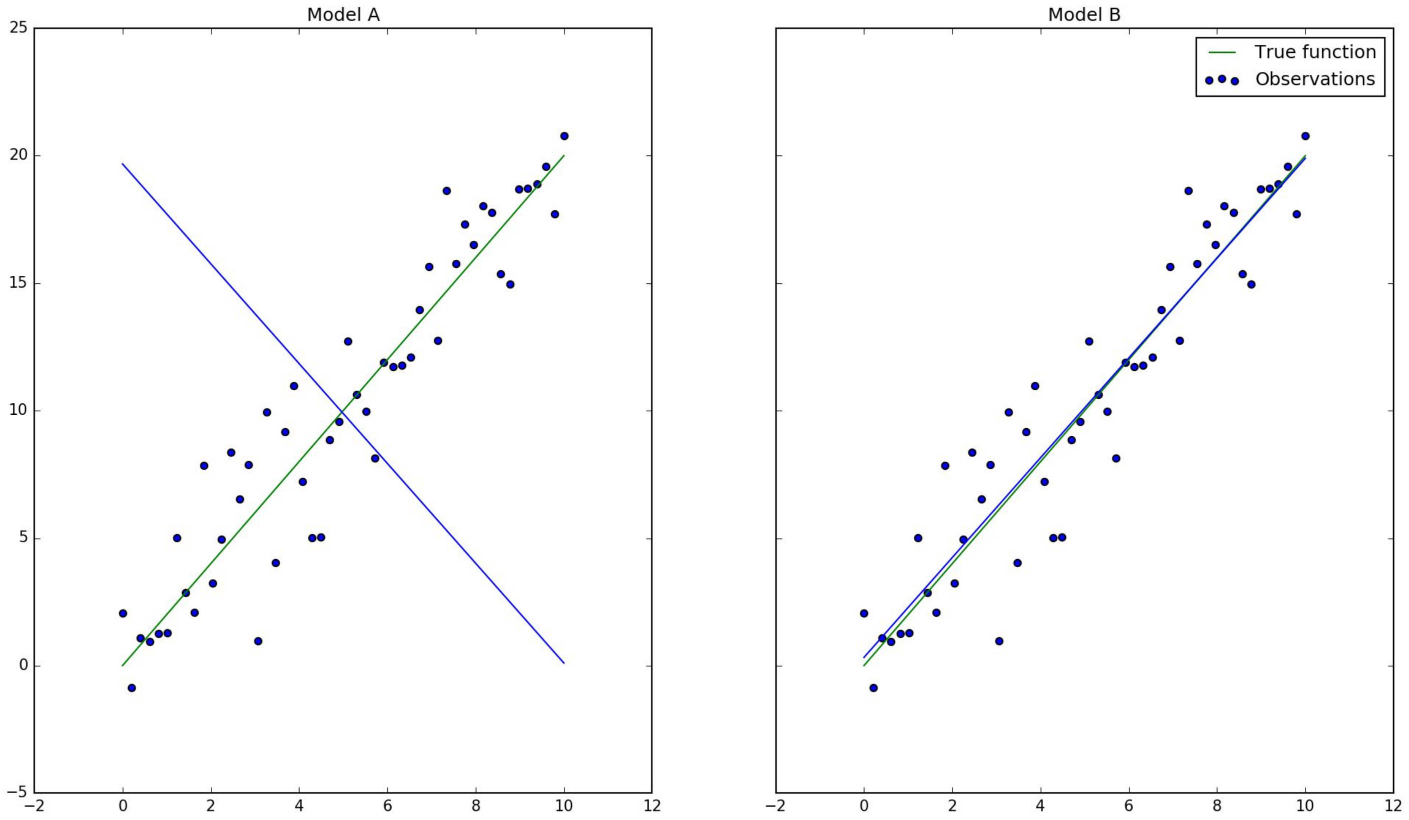


How accurate is it?

Measuring Error

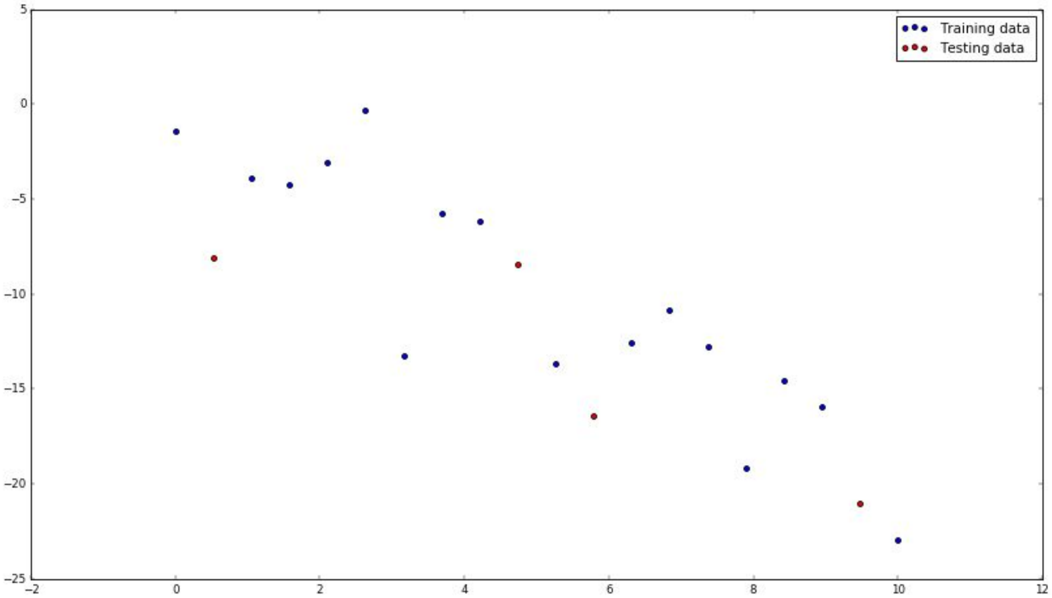


Measuring Error



Measuring Error

- Hold out some “testing data”

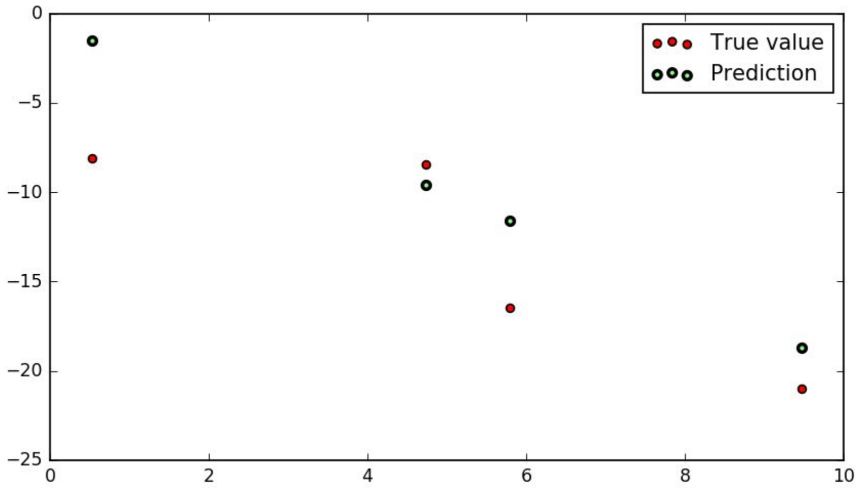


Measuring Error

- Hold out some “testing data”
- Compare test data to prediction
- Ideally: calculate the real cost of an error
  - Cost of false positive in nuclear warhead detection: **HIGH**
  - Cost of false positive in fingerprint recognition on my phone: **SIGNIFICANTLY LOWER**

Measuring Error

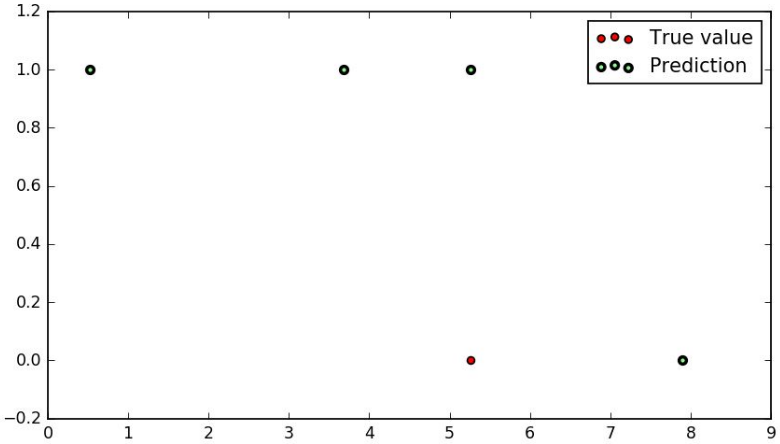
- Compare test data to prediction
- Common metric for regression: mean squared error
  - 18.35



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

Measuring Error

- Compare test data to prediction
- Common metric for classification: mean classification error
  - 0.25



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 allows for evaluation

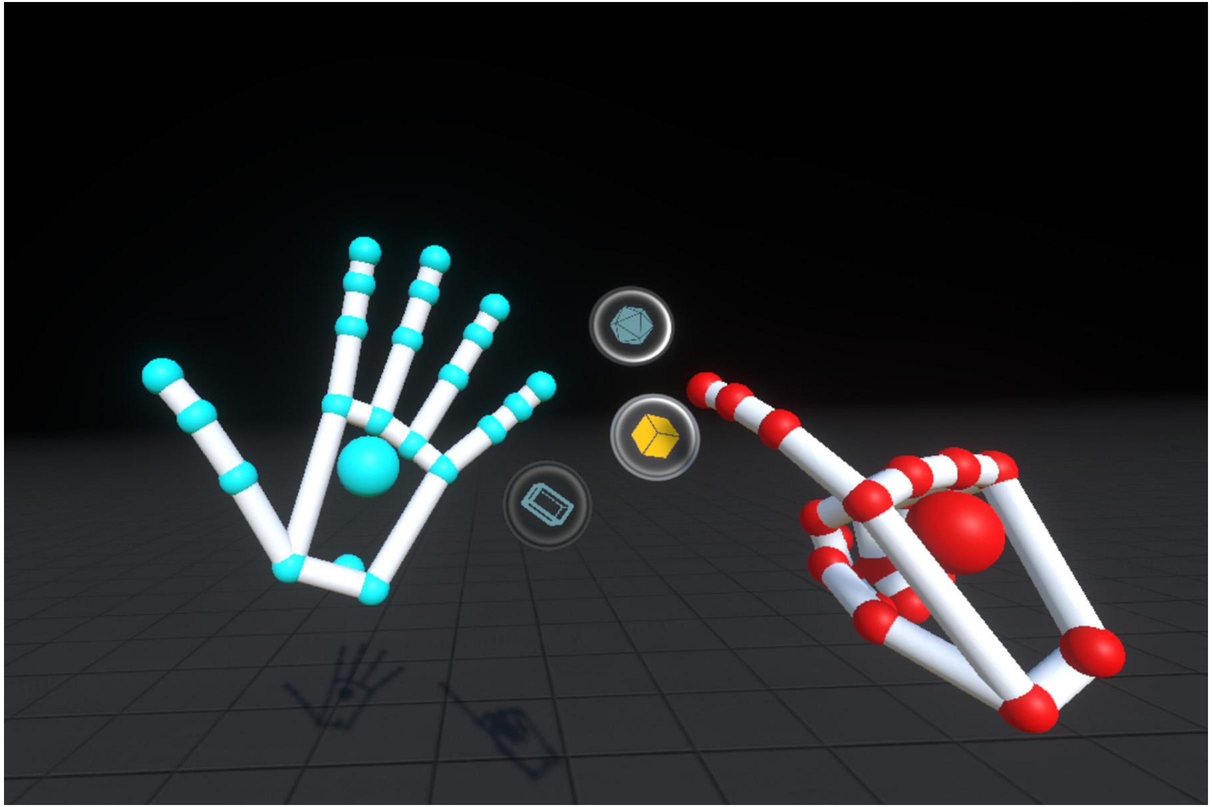
UC1: Teach a computer sign language

UC1: Teach a computer sign language

- What’s the problem?
  - I don’t know sign language
  - I want to communicate with deaf people
- What does the data look like?
- What kind of ML problem is this?
- Solution
- Lessons learned

UC1: What does the data look like?

UC1: What does the data look like?



UC1: 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

So… what kind of ML problem is this?

UC1: 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
- Build an application
  - Keyboard… not so great
  - But! It’s good enough to make an educational game


Great job! Now try "x".

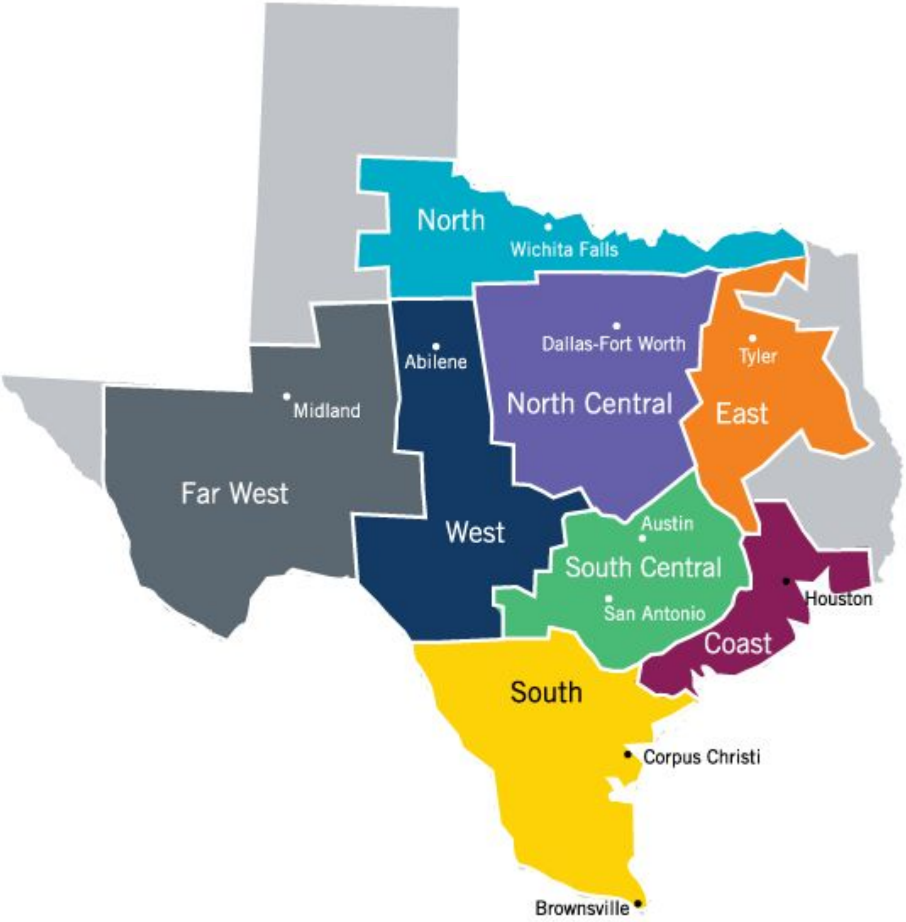
UC1: Lessons learned

- Limit scope
- Model selection
- It’s more than the model

UC2: Forecast energy load in Texas

UC2: Forecast energy load

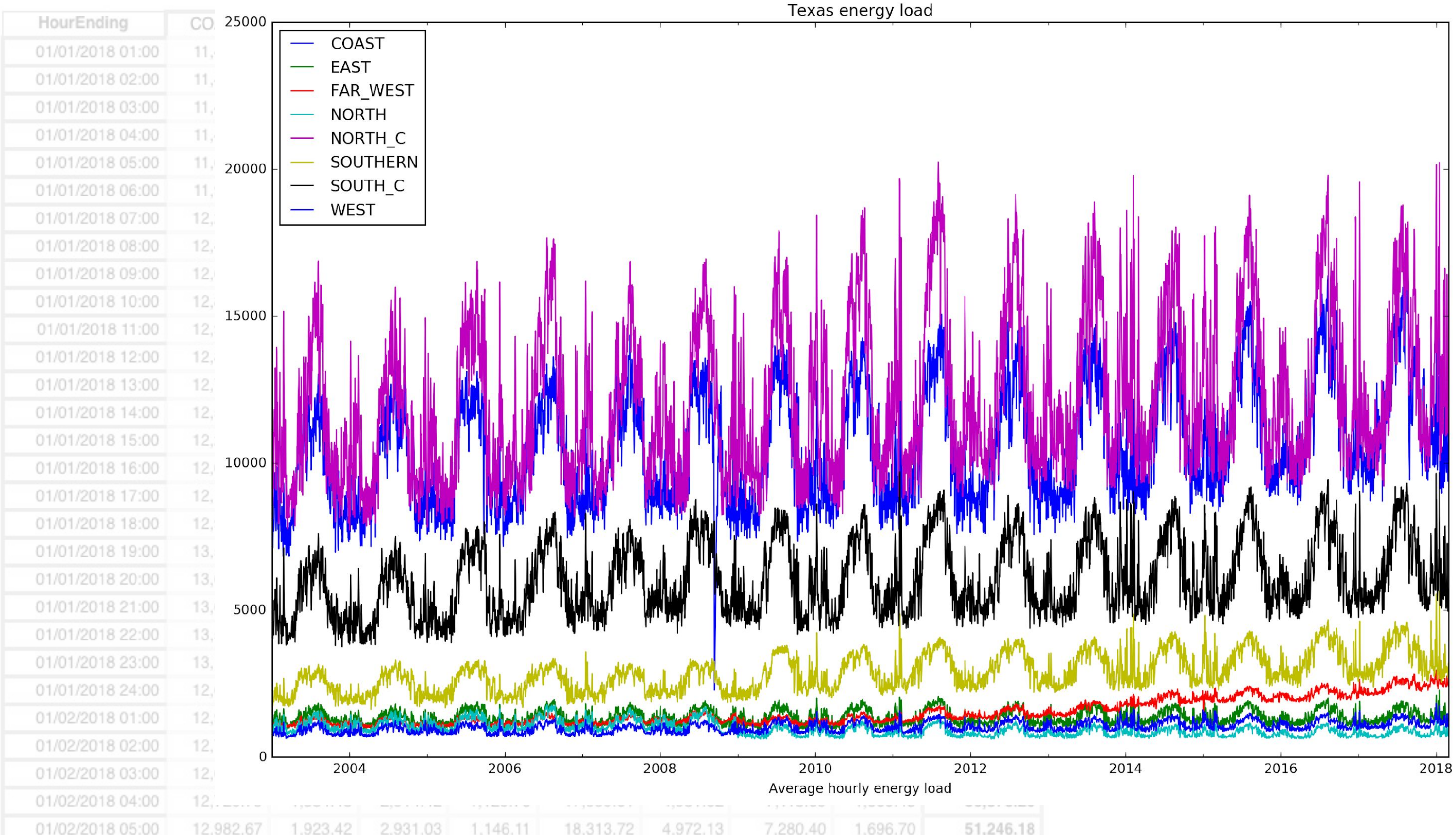
- What's the problem?
  - Suppose I operate a power grid
  - Have to know demand to schedule production
- What does the data look like?
- What kind of ML problem is this?
- Solution
- Lessons learned


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

UC2: 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**
01/02/2018 01:00	12,954.54	1,877.85	2,908.41	1,109.40	18,245.55	5,105.51	7,348.84	1,630.07	**51,180.17**
01/02/2018 02:00	12,762.33	1,863.55	2,896.25	1,112.72	18,041.58	5,011.84	7,172.20	1,632.21	**50,492.67**
01/02/2018 03:00	12,672.32	1,870.35	2,903.21	1,121.27	17,954.64	4,964.11	7,093.98	1,640.71	**50,220.58**
01/02/2018 04:00	12,720.79	1,884.48	2,914.42	1,129.76	17,999.01	4,951.62	7,115.69	1,660.43	**50,376.20**
01/02/2018 05:00	12,982.67	1,923.42	2,931.03	1,146.11	18,313.72	4,972.13	7,280.40	1,696.70	**51,246.18**

UC2: What does the data look like?



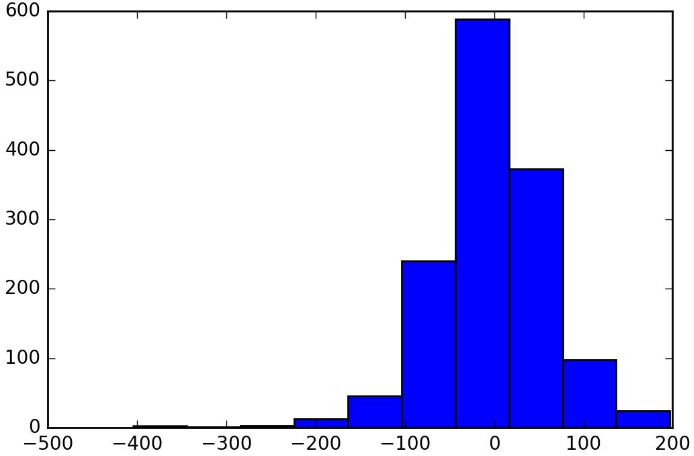
So… what kind of ML problem is this?

UC2: A simple approach

- Given a day, take the average of the 5 nearest days
  - *k*-Nearest Neighbors
- Nearest = closest day number
  - e.g. 10 Apr 2018 is day #100 of 2018

UC2: Accuracy

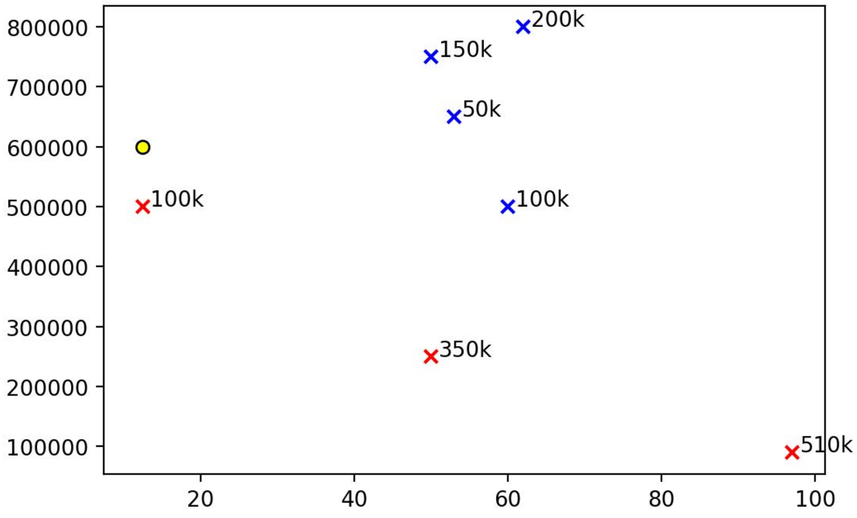
- Mean absolute error: ~3%
- Residuals
  - predicted - actuals
  - Goal: no pattern

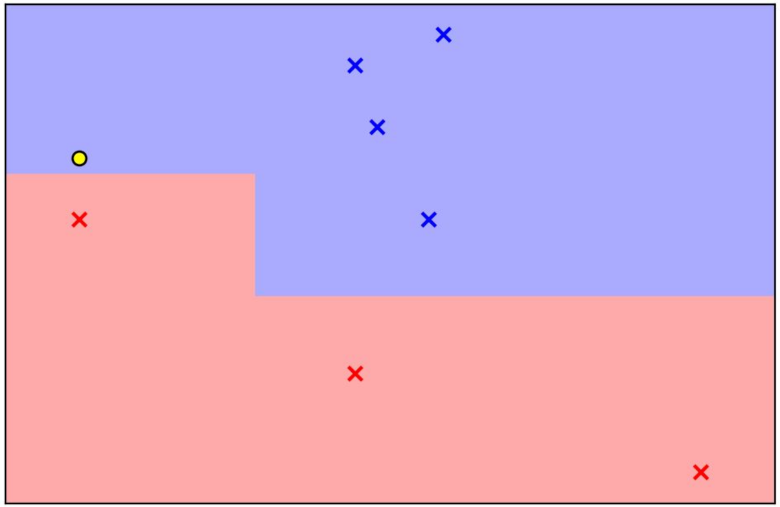


UC2: Lessons learned

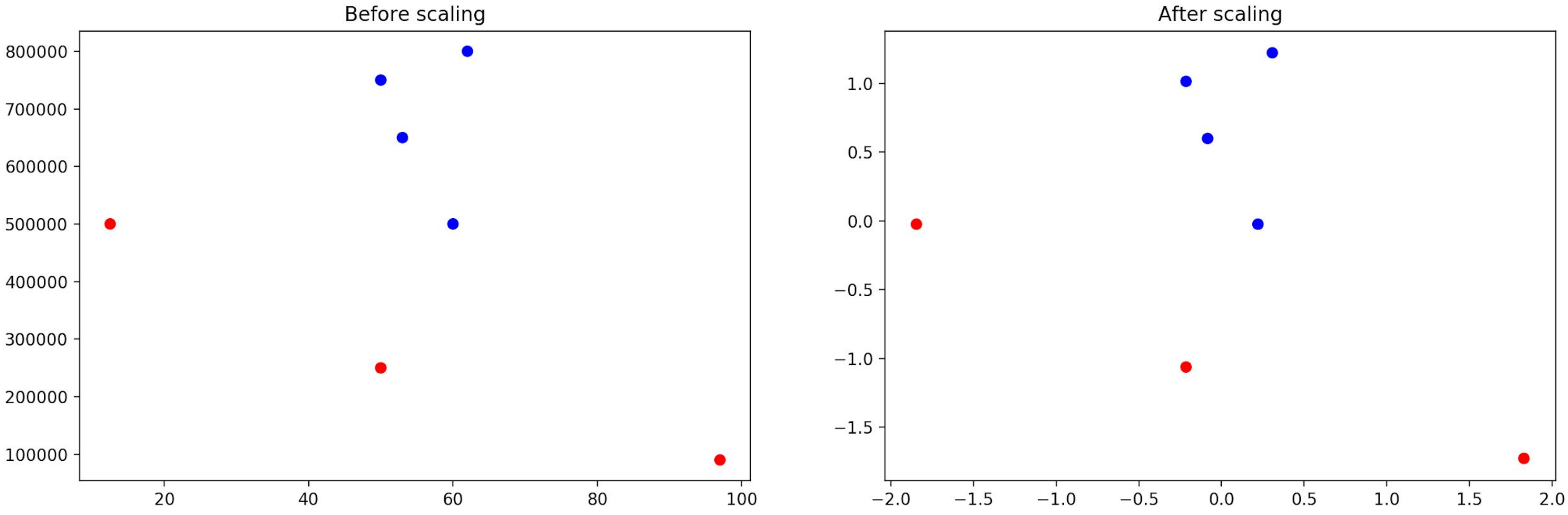
- Do your research!
    - Look into Prophet (Facebook) and/or CausalImpact (Google)
- Scale your features

UC2: Scaling features

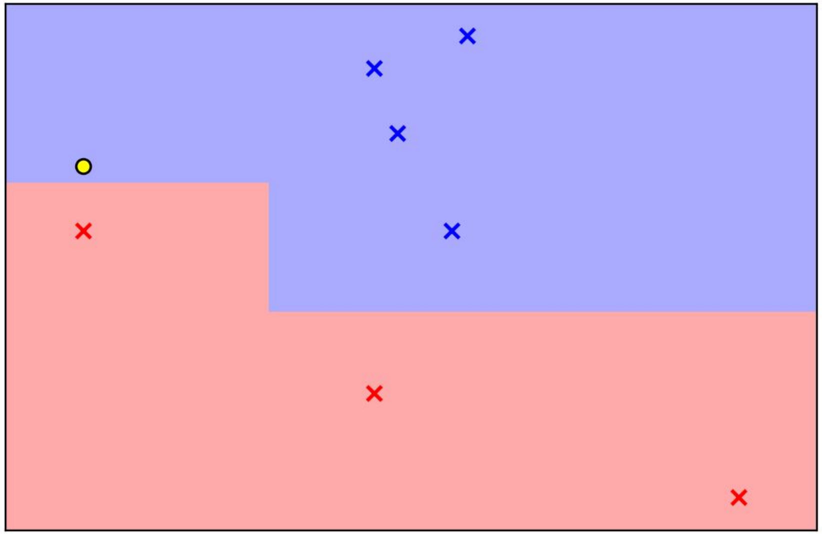


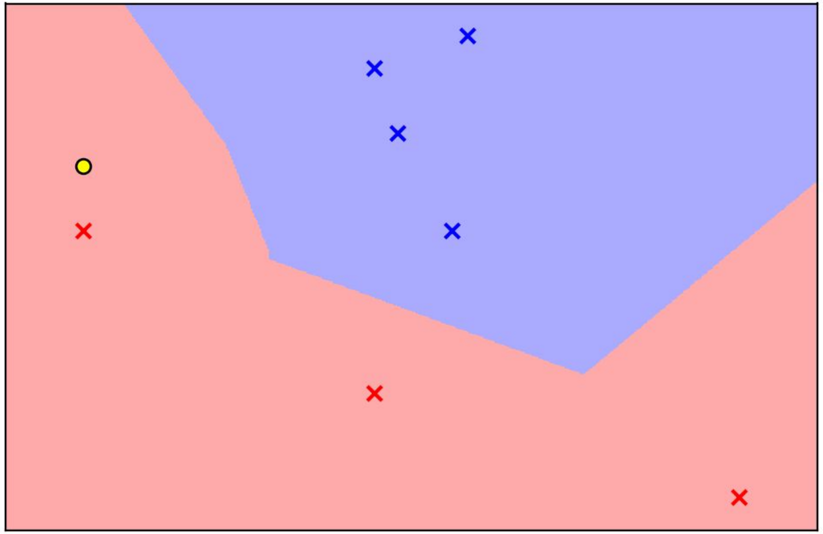


UC2: Scaling features



UC2: Scaling features





UC3: Use machine learning to find your next job

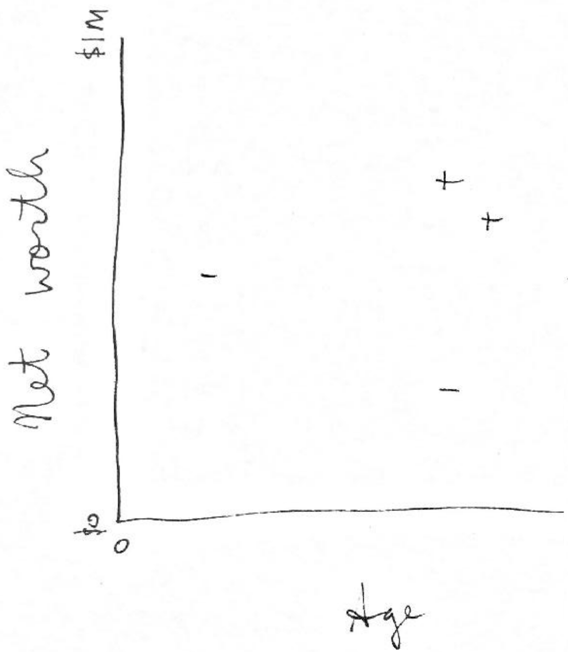
UC2: Forecast energy load

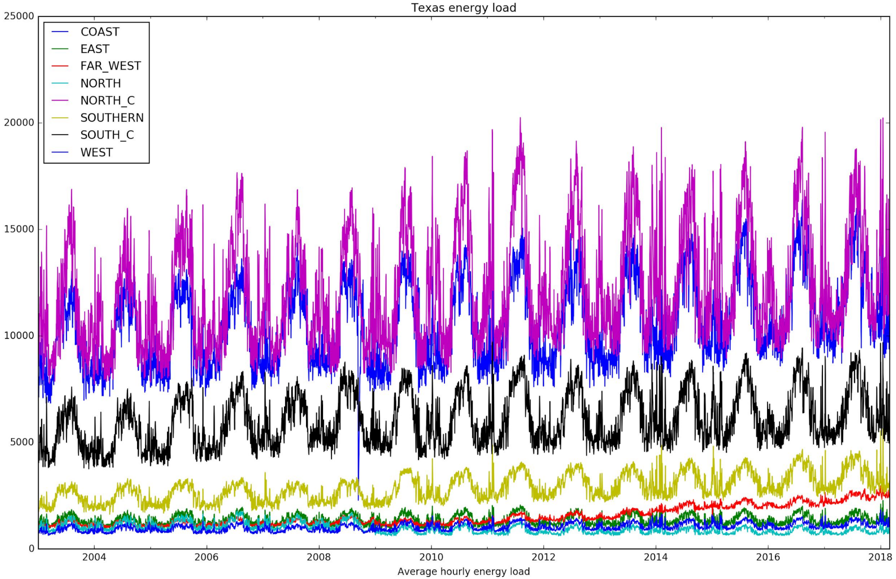
- What's the problem?
  - Passive job hunting
- What does the data look like?
- What kind of ML problem is this?
- Solution
- Lessons learned

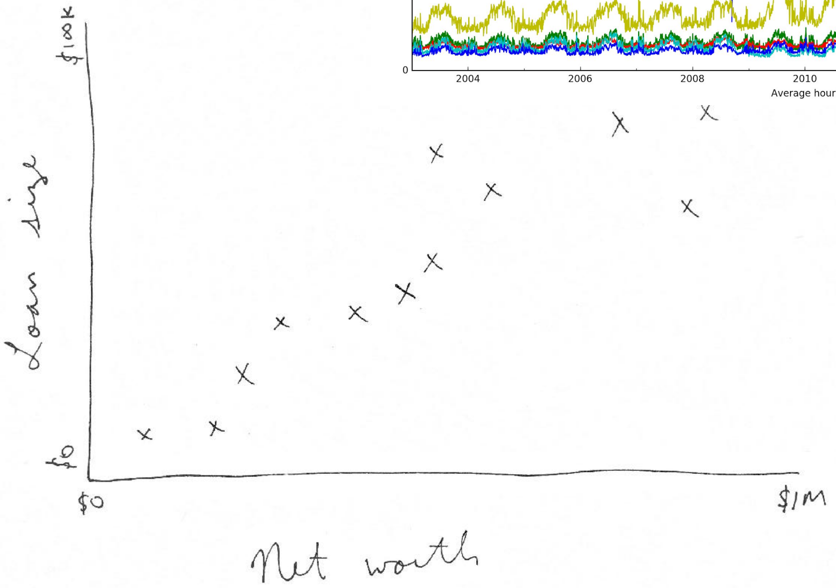
	A	B	C	D	E
1	**Title**	**Company**	**U**	**Link**	**Sounds cool**
2	Principal Software Architect - Austin	General Electric	/r	Link	1
3	ASIC Power Estimation Developer (Excel-I	Encore Semi	/r	Link	0
4	Memory Subsystem Verification Engineer	Encore Semi	/r	Link	0
5	Senior DevOps Engineer	KIBO Software	/r	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
18	Software Development Engineer - Silicon (	Amazon Corporate LLC	/r	Link	0
19	Software Developer	IBM	/r	Link	0
20	Sr. Product Development Engineer	Advanced Micro Devices, Inc.	/r	Link	0
21	Front end developer	IBM	/r	Link	0
22	Full Stack Software Engineer	Indeed	/r	Link	1

So… what kind of ML problem is this?

UC3: Solution


$1M
Net worth
$0
0
Age


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


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

(Sr. Data Engineer, 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

(Sr. Data Engineer, sounds_cool=True)

⬇

(1, 0, 0, 1, 0, 0, 0, 1, 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.,  0.,  0.])
```

UC3: Solution – Accuracy

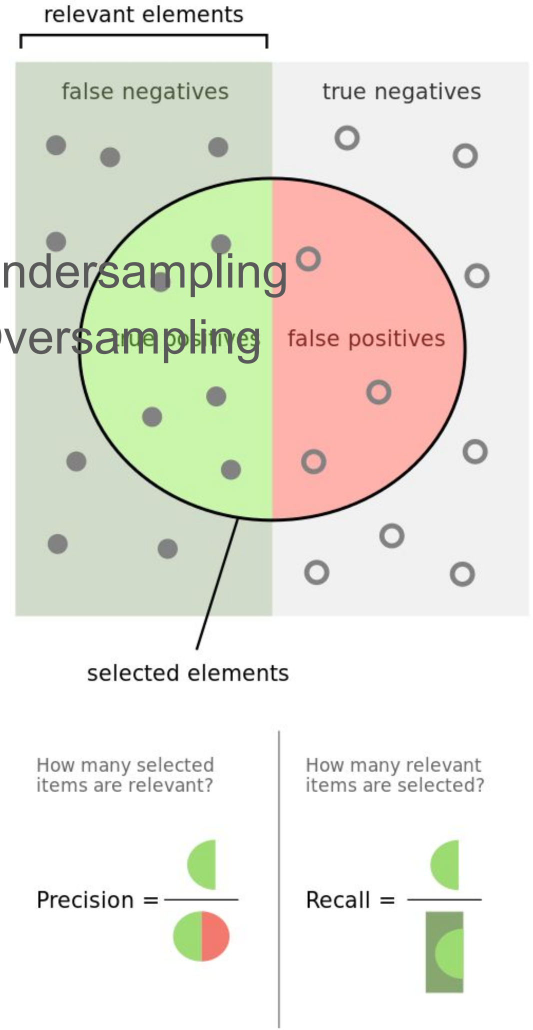
- Classification error: 0.197
    - Awesome!
- But wait, it’s just classifying everything as “not cool”
- Base rate for this problem is 0.197
    - No improvement

Handling imbalanced classes

- Better error metrics
  - Precision
  - Recall
  - Confusion matrix

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

- Undersampling
- Oversampling



Walber

UC3: 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

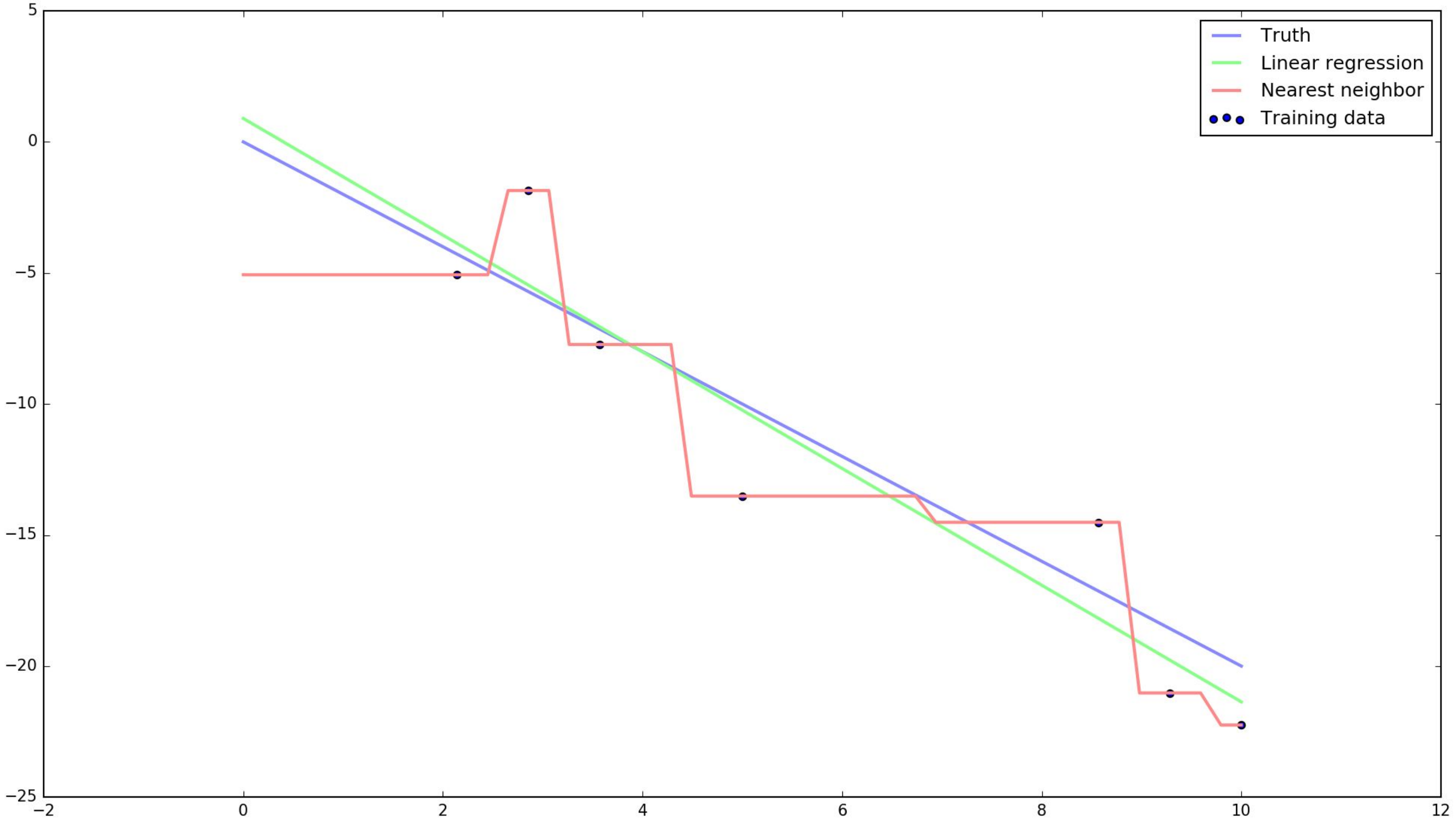
Software Development Principal Engineer - Austin, TX @ Dell - https://dell.taleo.net/careersection/2/jobdetail.ftl?job=17000FQB&tz=GMT-05:00&src=JB-11346

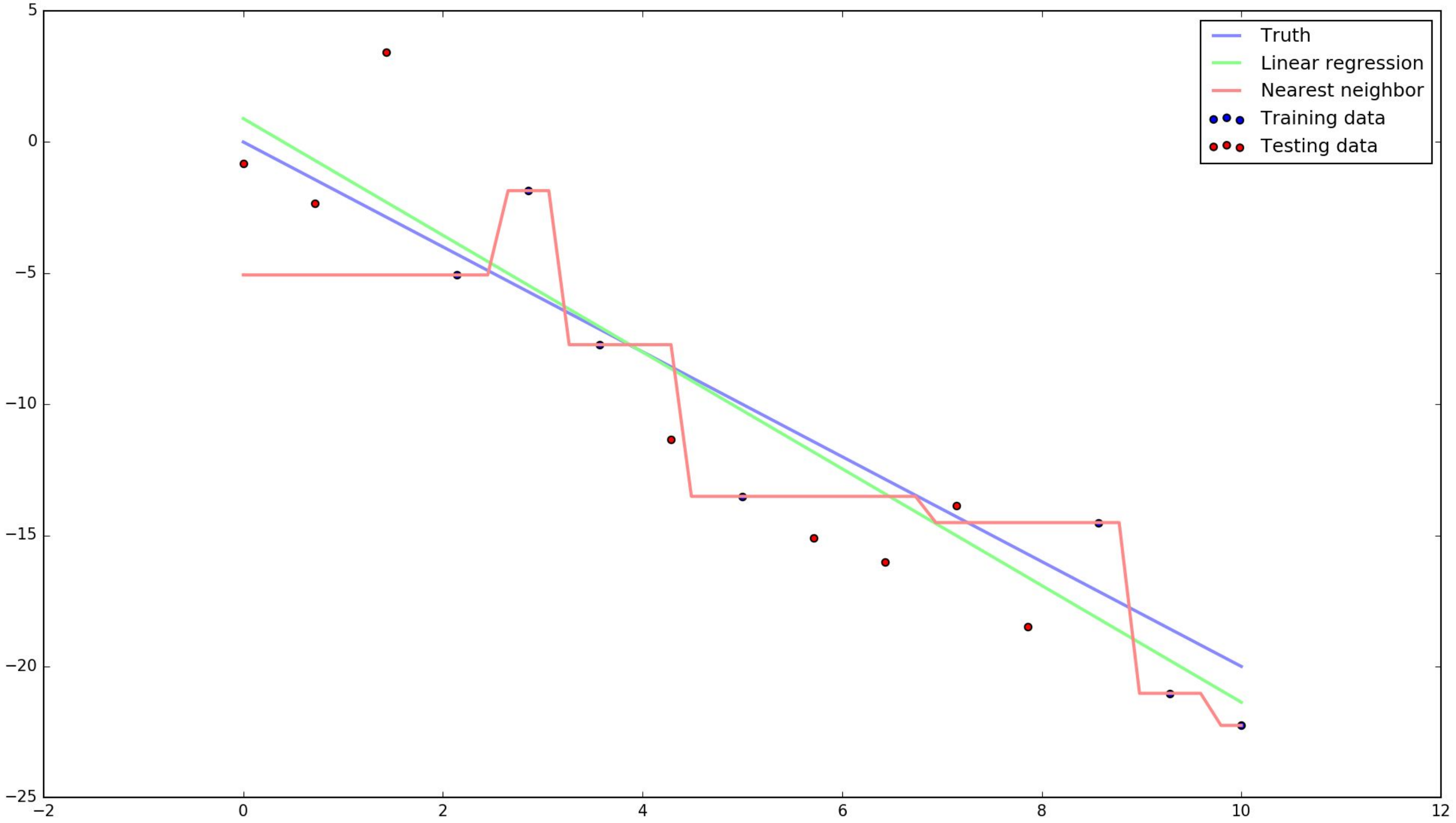
UC3: Lessons learned

- Understand the base rate
- Simple doesn’t mean ineffective

UC3: Keep it simple, stupid

- Approximation-generalization tradeoff


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



Truth
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8
10
12

Theory

- Approximation-generalization tradeoff
- It’s just easier

Summary

- **UC1:** Teach a computer sign language
  - Support vector machines
- **UC2:** Forecast energy load in Texas
  - Time series data
  - *k*-nearest neighbors
- **UC3:** Use machine learning to find your next job
  - Text data; bag of words
  - Logistic regression

Theory

- Approximation-generalization tradeoff
- It's just easier

Practice

- Start with simple models
  - Linear regression
  - Logistic regression

Takeaways

Recommended tools

- Supervised learning uses past examples to predict a continuous or discrete value
- Try the simplest thing that could possibly work
- Test and iterate

Takeaways

- Supervised learning uses past examples to predict a continuous or discrete value
- Try the simplest thing that could possibly work
- Test and iterate

Recommended tools

- Jupyter Notebook
- Pandas
- scikit-learn

More resources

- Learning from Data
- Practical Business Python
- Kaggle blog
- ASL Tutor (more info on teaching a computer sign language)
- Use Machine Learning to Find Your Next Job

indeed®

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