# A quick introduction to machine learning Spyros Samothrakis Senior Lecturer, IADS University of Essex MiSoC

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Tuning

# Welcome/course contents

- ▶ What will this course cover?
  - ▶ Day 1: An intro to machine learning (ML)
  - ► Day 1: ML labs
  - ▶ Day 2: An intro to causal inference
  - ► Day 2: ML and causal inference labs
- ► Textbooks?
  - ▶ Mitchell, T. M. (1997). Machine learning.¹
  - Bishop, C. M. (2006). Pattern recognition and machine learning. springer.<sup>2</sup>
  - ► Wasserman, L. (2013). All of statistics: a concise course in statistical inference. Springer Science & Business Media.<sup>3</sup>

<sup>1</sup>http://www.cs.cmu.edu/~tom/mlbook.html

 $<sup>^2 \</sup>verb|https://www.microsoft.com/en-us/research/publication/pattern-recognition-machine-learning/$ 

<sup>3</sup>http://www.stat.cmu.edu/~larry/all-of-statistics/index.html

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Hey, Tony, Stewart Tansley, and Kristin M. Tolle. "Jim Gray on eScience: a transformed scientific method." (2009).<sup>4</sup>

- ► Thousand years ago: empirical branch
  - ► You observed stuff and you wrote down about it
- ► Last few hundred years: theoretical branch
  - ► Equations of gravity, equations of electromagnetism
- ► Last few decades: computational branch
  - ▶ Modelling at the micro level, observing at the macro level
- ► Today: data exploration
  - ▶ Let machines create models using vast amounts of data

<sup>4</sup>http://languagelog.ldc.upenn.edu/myl/JimGrayOnE-Science.pdf

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#### BETTER BUSINESS THROUGH DATA

► There was a report by Mckinsey

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Hung Byers, A. (2011). Big data: The next frontier for innovation, competition, and productivity. McKinsey Global Institute.<sup>5</sup>

HIGHER DIMENSIONS

- ▶ Urges everyone to monetise "Big Data"
- ▶ Use the data provided within your organisation to gain insights
- ► Has some numbers as to how much this is worth
- ▶ Proposes a number of methods, most of them associated with machine learning and databases

 $<sup>^5 \</sup>mathrm{http://www.mckinsey.com/business-functions/digital-mckinsey/our-}$ insights/big-data-the-next-frontier-for-innovation

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## WHY IS IT POPULAR NOW?

- ightharpoonup Algorithms + data + tools
- ▶ Breiman, L. (2001). Statistical modeling: The two cultures (with comments and a rejoinder by the author). Statistical science, 16(3), 199-231.
- $\blacktriangleright$  Anderson, P. W. (1972). More is different. Science, 177(4047), 393-396.  $^7$
- ► Pedregosa, et.al. (2011). Scikit-learn: Machine learning in Python. the Journal of machine Learning research, 12, 2825-2830.8

 $<sup>^6 \</sup>rm http://projecteuclid.org/download/pdf_1/euclid.ss/1009213726%20 <math display="inline">^7 \rm https:$ 

<sup>//</sup>www.tkm.kit.edu/downloads/TKM1\_2011\_more\_is\_different\_PWA.pdf  $^8 \rm https:$ 

<sup>//</sup>www.jmlr.org/papers/volume12/pedregosa11a/pedregosa11a.pdf

Introduction Some algorithms Higher dimensions Testing Tuning Wrapping up

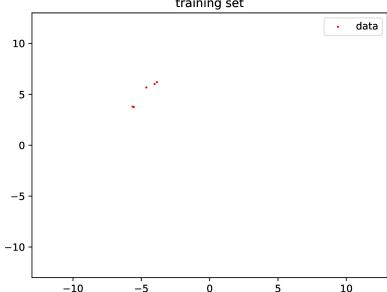
#### WHAT WILL WE COVER?

- ► ML background
  - ► Supervised learning
    - ightharpoonup Regression
    - ightharpoonup Classification
  - ► Understanding basic modelling
  - ► Confirming your model is sane
  - ► Tuning your model
  - ► All within a very applied setting
- ► Tools
  - ► Numpy
  - ► Scikit-learn

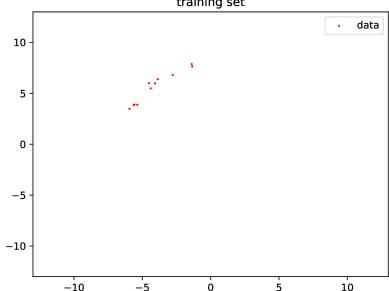
## WHAT IS SUPERVISED LEARNING?

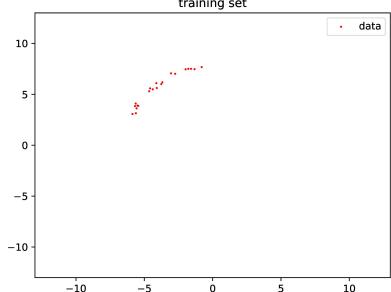
- ► Imagine someone gives you data from a group of smokers
- ► What is their life expectancy?
- ▶ We are given inputs  $x_0, x_1...x_n$  and we are looking to predict y
- ▶ The problem alludes to certain statistical concepts
- ► Let's plot some imaginary data



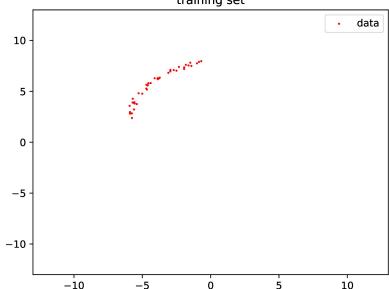






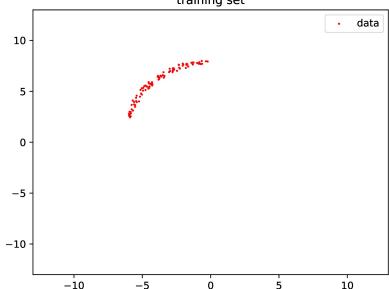




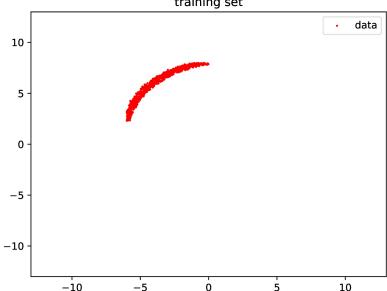


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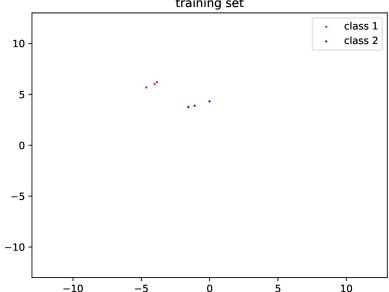




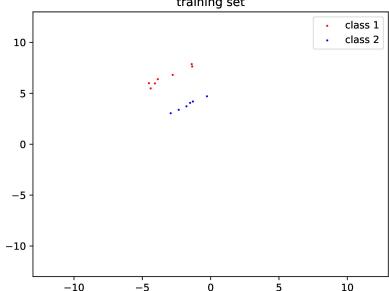




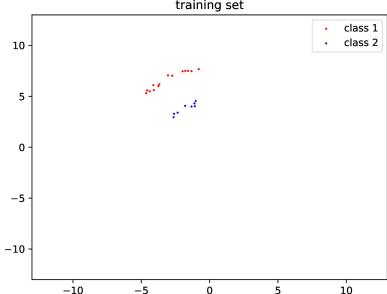




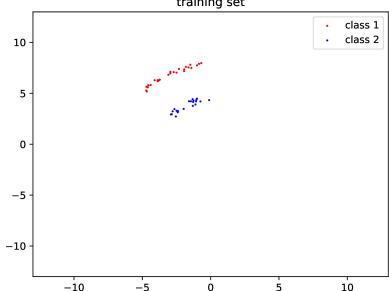


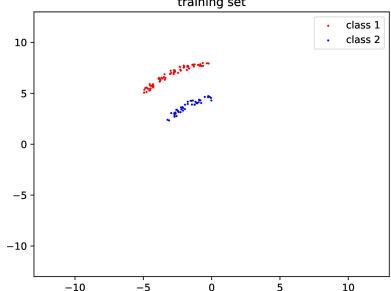


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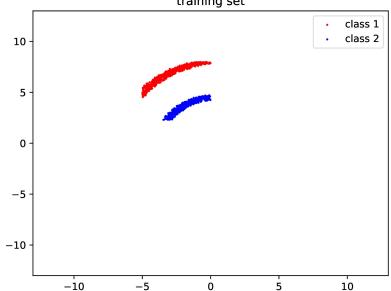




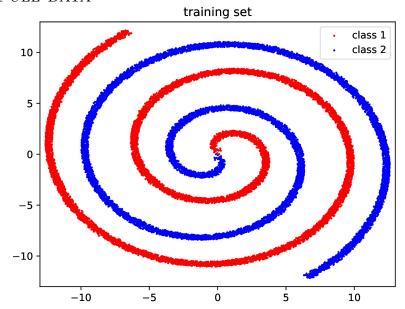






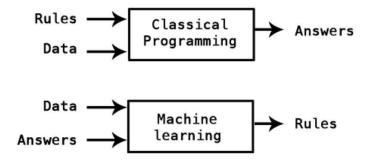


## Full data



# Intuition (1)

Chollet, F. (2018). Deep learning with Python (Vol. 361). New York: Manning.  $^9$ 



 $<sup>^9 {</sup>m https://www.manning.com/books/deep-learning-with-python}$ 

Introduction Some algorithms Higher dimensions Testing Tuning Wrapping up

# Intuition (2)

- ► That's it we are given data, and we need to come up with an algorithm to join it up but in high dimensions
  - ► Can can be binary, categorical, real-valued more on this later
- ► How well well a function joins the data is called the "loss"
- ► Multiple solutions exist, so a loss function must take into account concepts other than pure fit

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### VS CAUSALITY

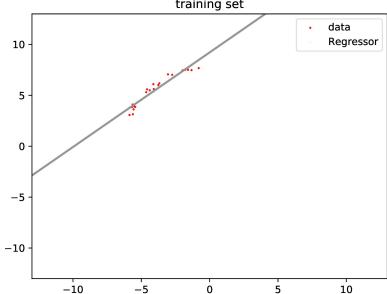
- ► Imagine someone gives you data from a group of smokers
  - ► What is their life expectancy?
  - ► Is smoking bad for you?
- ► You could potentially just do predictions using correlations
  - ► What if there was a gene that caused early death and also made you like smoking?
  - ► More on this tomorrow

HIGHER DIMENSIONS

## LINEAR REGRESSION

- ► Linear and logistic regression
  - ► Logistic regression does classification
- ► You just assume everything is a line
- ightharpoonup f(x) = wx + b

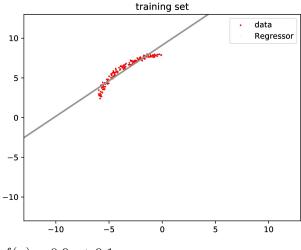




HIGHER DIMENSIONS

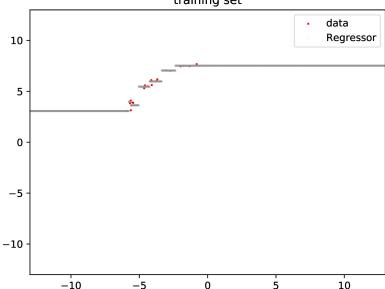
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# EXAMPLE (LINEAR REGRESSION)

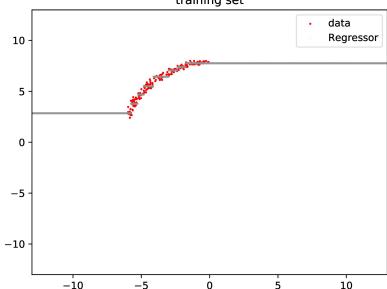


$$f(x) = 0.9x + 9.1$$



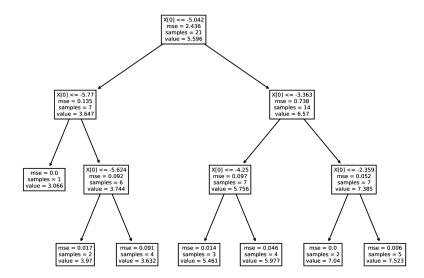




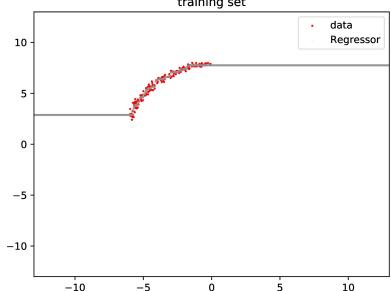


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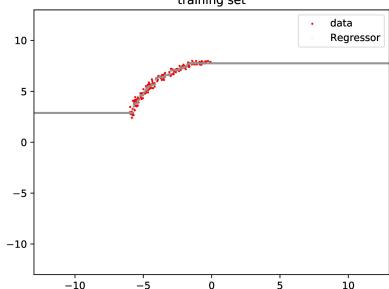
HIGHER DIMENSIONS



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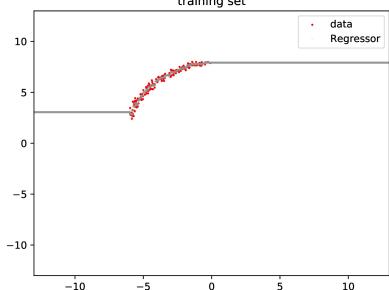




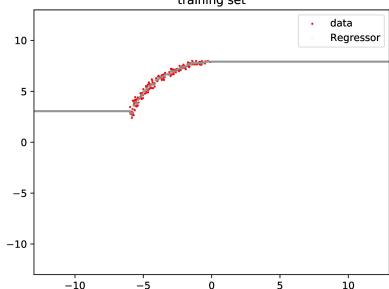


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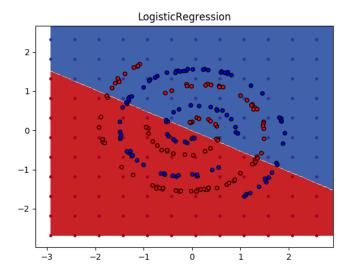


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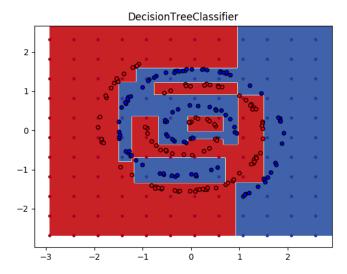


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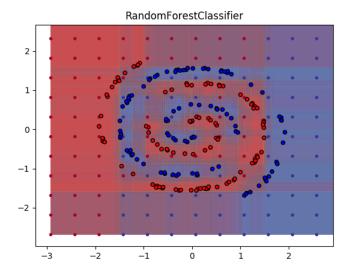
# CLASSIFICATION (LOGISTIC REGRESSION)



# CLASSIFICATION (DECISION TREES)



# CLASSIFICATION (RANDOM FORESTS)



#### DATA DIMENSIONALITY

- ► Until now we have seen input data of 1 (for regression) or two (for classification) dimensions
- ► How about higher dimensional data?
  - ► Some times data can have millions of features
- ► Let's examine more high dimensional dataset
- ► Visualisation becomes harder

Feature	Description
$\overline{X_0}$	Pregnancies: Number of times pregnant
$X_1$	Glucose: Plasma glucose concentration
$X_2$	BloodPressure: Diastolic blood pressure (mm Hg)
$X_3$	SkinThickness: Triceps skin fold thickness (mm)
$X_4$	Insulin: 2-Hour serum insulin (mu U/ml)
$X_5$	BMI: Body mass index (weight in kg/(height in m)^2)
$X_6$	DiabetesPedigreeFunction: Diabetes pedigree function
$X_7$	Age: Age (years)
y .	Outcome: Has diabetes (0 or 1)

https://www.kaggle.com/mathchi/diabetes-data-set

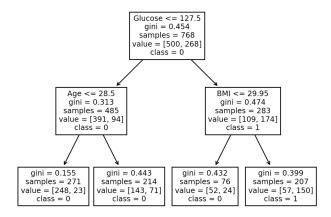
### HOW DOES THE DATA LOOK LIKE?

	Pregnancies	Glucose	${\bf BloodPressure}$	${\bf Skin Thickness}$	Insulin	BMI	DPF	Age
0	6	148	72	35	0	33.60	0.63	50
1	1	85	66	29	0	26.60	0.35	31
2	8	183	64	0	0	23.30	0.67	32
3	1	89	66	23	94	28.10	0.17	21
4	0	137	40	35	168	43.10	2.29	33

HIGHER DIMENSIONS

HIGHER DIMENSIONS

### DECISION TREE



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### DIABETES REGRESSION

Introduction

Efron, B., Hastie, T., Johnstone, I., & Tibshirani, R. (2004). Least angle regression. Annals of statistics, 32(2), 407-499.<sup>10</sup>

Feature	Description
$\overline{X_0}$	age in years
$X_1$	sex
$X_2$	bmi body mass index
$X_3$	bp average blood pressure
$X_4$	s1 tc, total serum cholesterol
$X_5$	s2 ldl, low-density lipoproteins
$X_6$	s3 hdl, high-density lipoproteins
$X_7$	s4 tch, total cholesterol / HDL
$X_8$	s5 ltg, possibly log of serum triglycerides level
$X_9$	s6 glu, blood sugar level
y	disease progression one year after baseline

<sup>10</sup> https:

<sup>//</sup>scikit-learn.org/stable/datasets/toy\_dataset.html#diabetes-dataset

	age	sex	bmi	bp	s1	s2	s3	s4	s5	s6
0	0.04	0.05	0.06	0.02	-0.04	-0.03	-0.04	-0.00	0.02	-0.02
1	-0.00	-0.04	-0.05	-0.03	-0.01	-0.02	0.07	-0.04	-0.07	-0.09
2	0.09	0.05	0.04	-0.01	-0.05	-0.03	-0.03	-0.00	0.00	-0.03
3	-0.09	-0.04	-0.01	-0.04	0.01	0.02	-0.04	0.03	0.02	-0.01
4	0.01	-0.04	-0.04	0.02	0.00	0.02	0.01	-0.00	-0.03	-0.05

HIGHER DIMENSIONS

"Note: Each of these 10 feature variables have been mean centered and scaled by the standard deviation times n\_samples (i.e. the sum of squares of each column totals 1)."

	У
0	151.00
1	75.00
2	141.00
3	206.00
4	135.00

### LINEAR REGRESSION

Introduction

$$y = -210x_0 - 5036x_1 + 10916x_2 + 6812x_3 - 16635x_410011x_5 + 2121x_6 + 3718x_7 + 15776x_8 + 1420x_9 + 152$$

### QUALITY ASSESSMENT

- ► In lower dimensions, the visualisations we did provided some insights to the quality of our methods
  - ► This is impossible in higher dimensions
- ► We need to measure some kind of metric that denotes quality of fit

### Metrics

- ► For regression,
  - ► Mean Squared Error
  - ► Mean Absolute Error
- ► For classification
  - ► Accuracy
  - ► Mean Squared Error
  - ► Cross-entropy loss
  - ► AUC
- ► Each one has different benefits, e.g. absolute errors tend to be more robust to outliers

### ACCURACY

 $\blacktriangleright$  Our model is  $\hat{f}(x)$ , x are examples, y is outcome

Higher dimensions

- ► Accuracy is the obvious one
  - $accuracy = \frac{1}{N} \sum_{i=0}^{N-1} (y_i = \hat{f}(x))$
  - ► The higher the accuracy the better
- ▶ What if the dataset is unbalanced how informative is accuracy then?
- ► There are multiple score functions
  - ▶ Use the one appropriate for your problem

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# MEAN SQUARED ERROR (MSE)

• Our model is  $\hat{f}(x)$ , x are examples, y is outcome

$$MSE = \frac{1}{N} \sum_{i=1}^{N} \left( y_i - \hat{f}(x_i) \right)^2$$

## TRAIN/VALIDATION/TEST SPLIT

- ▶ Basic idea: split your data into three portions
- ▶ 1. train, you used that to train your classifier/regressor
- ▶ 2. validation, you use that to assess the quality of your method, retraining as you see fit
- ▶ 3. test, you report results on this
- $\triangleright$  Common split is 60%/20%/20%

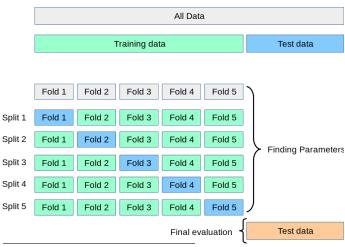
Introduction Some algorithms

### Cross validation

- ► How about we split our data into multiple validation sets and find the mean?
  - ► Instead of having just one split train/test split, we can have multiple
- ► Colloquially goes by names like 5-fold CV, 10-fold CV
- ► There are multiple ways of doing the sampling to create training/validation sets, we will focus on only one

#### Pictorial Depiction of 5-fold CV

Copied from SKlearns website<sup>11</sup>



<sup>11</sup>https:

//scikit-learn.org/stable/\_images/grid\_search\_cross\_validation.png

### WHY TUNE?

- ► Your data has peculiarities
- ▶ You need to "calibrate" your algorithm with these peculiarities
- ► Tuning properly will have a significant effect on cross-validation scores
  - ▶ ... and hence the quality of learning

Introduction Some algorithms

### Hyperparameters

- ► Called hyperparameters (vs parameters) as they influence how the modelling is done (vs the direct modeling)
  - ► How many trees?
  - ► Tree depth?
  - $\blacktriangleright$  Maximum tree size
  - ▶ 12 regularisation?
- ▶ vs parameters (e.g. weights in linear regression)

### WE NEED TO LOOK FOR OPTIMAL PARAMETERS

- ► Computationally expensive
- ► We can do this either by searching both the classifier/regressor space and their parameters
- ► Grid search
  - ▶ More than one parameter, we exhaustively search

### EXAMPLE USING LINEAR REGRESSION

alpha	scores	mean	std
0.0001	[2782, 3032, 3226, 3003, 2917]	2992.1772	145.5645
0.0001	[2783, 3032, 3223, 3002, 2920]	2992.0154	143.9139
0.0002	[2785, 3032, 3218, 3001, 2923]	2991.8400	141.7267
0.0007	[2812, 3042, 3186, 3002, 2945]	2997.5634	122.1458
0.0009	[2818, 3042, 3179, 2992, 2946]	2995.3784	117.9862
0.0012	[2827, 3043, 3178, 2978, 2947]	2994.6426	115.5067
0.0037	[2884, 3060, 3190, 2895, 2968]	2999.3816	114.1540
0.0049	[2918, 3079, 3201, 2869, 2985]	3010.3321	118.4097
0.0065	[2938, 3111, 3215, 2856, 3017]	3027.3294	126.2295
0.0085	[2966, 3152, 3219, 2859, 3057]	3050.5713	128.2733
0.0113	[3014, 3212, 3236, 2872, 3113]	3089.2555	134.1712
0.0149	[3028, 3292, 3279, 2918, 3201]	3143.7112	146.9126
0.0196	[3040, 3366, 3358, 2970, 3289]	3204.6848	166.7447
0.0259	[3082, 3493, 3484, 3074, 3435]	3313.4750	193.2530
0.0342	[3206, 3706, 3681, 3237, 3678]	3501.7398	229.0676
0.0452	[3434, 4030, 3972, 3448, 4037]	3784.1217	281.4318
0.0597	[3801, 4573, 4447, 3745, 4545]	4222.0278	369.6680
0.0788	[4401, 5460, 5212, 4299, 5425]	4959.4742	505.7819
0.1040	[5211, 6521, 6262, 5200, 6486]	5935.8770	603.2078
0.1374	[5353, 6521, 6262, 5290, 6486]	5982.4134	547.2524

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# What do you observer?

▶ Properly tuning your model can have a huge impact!

### Wrapping up

- ► You get data from somewhere
- ▶ ML will help you predict certain targets
- ► Data can be noisy
- ► You might need to pre-process it
- ► The more data the better
- ► Choosing the right classifier/regressor is important
  - ► Cross-validate and test