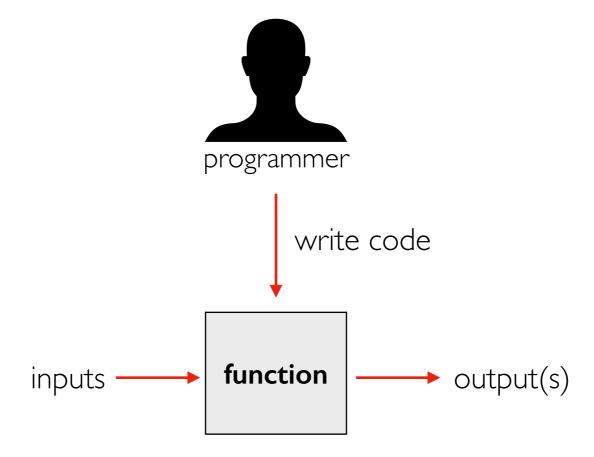
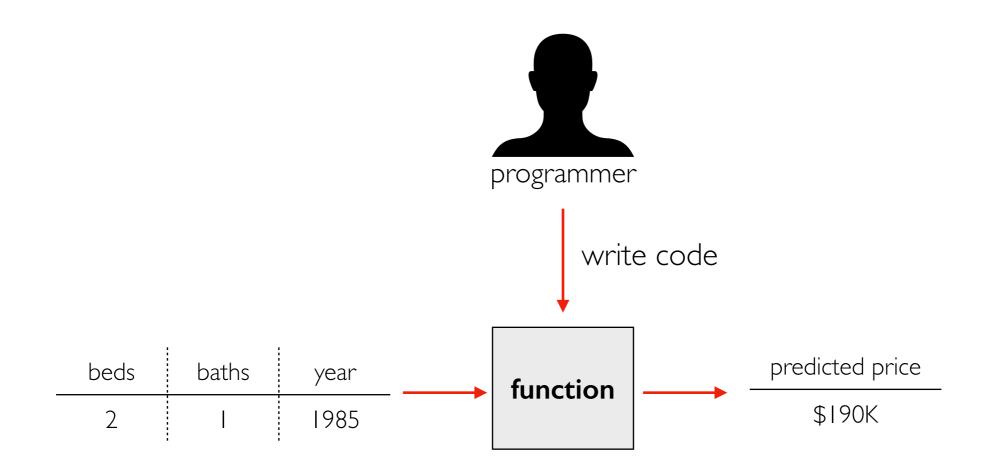
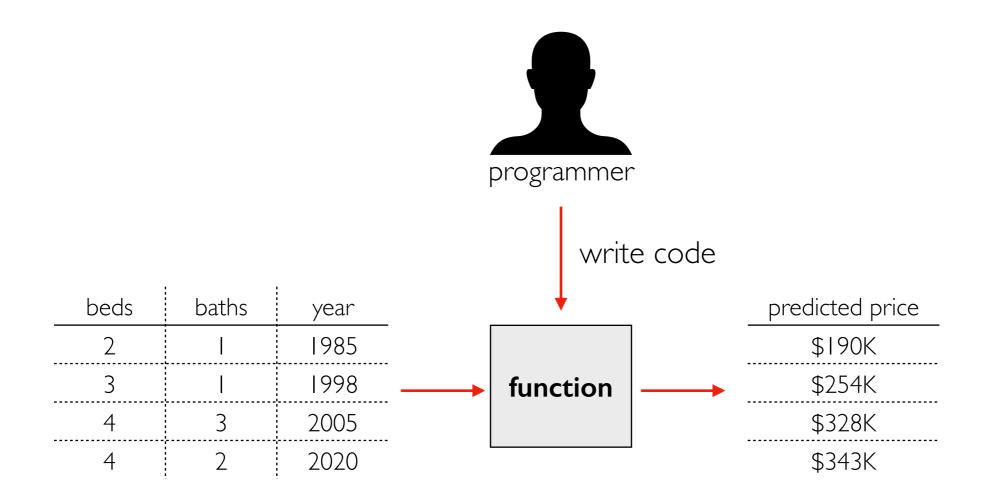
## [320] Machine Learning: Intro

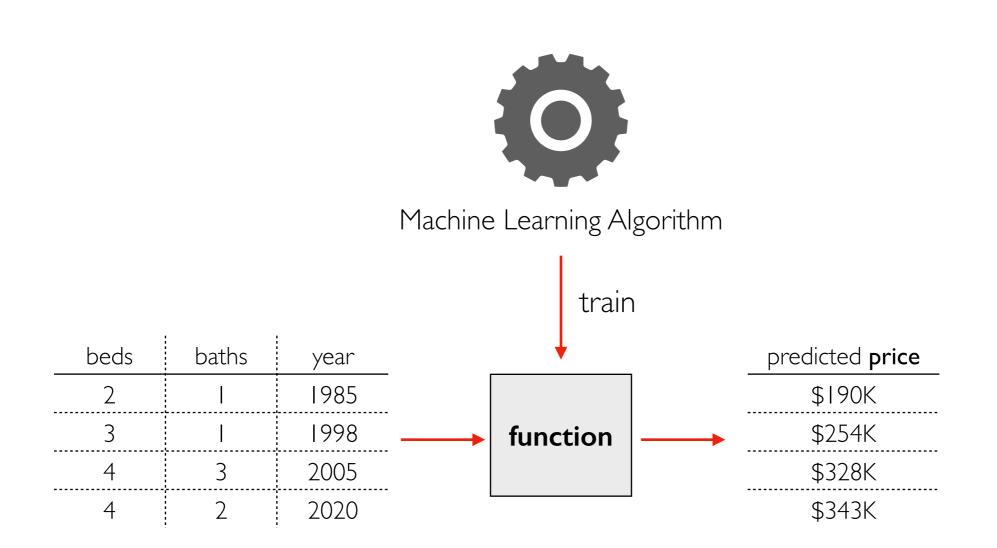
Tyler Caraza-Harter

## Functions/Models

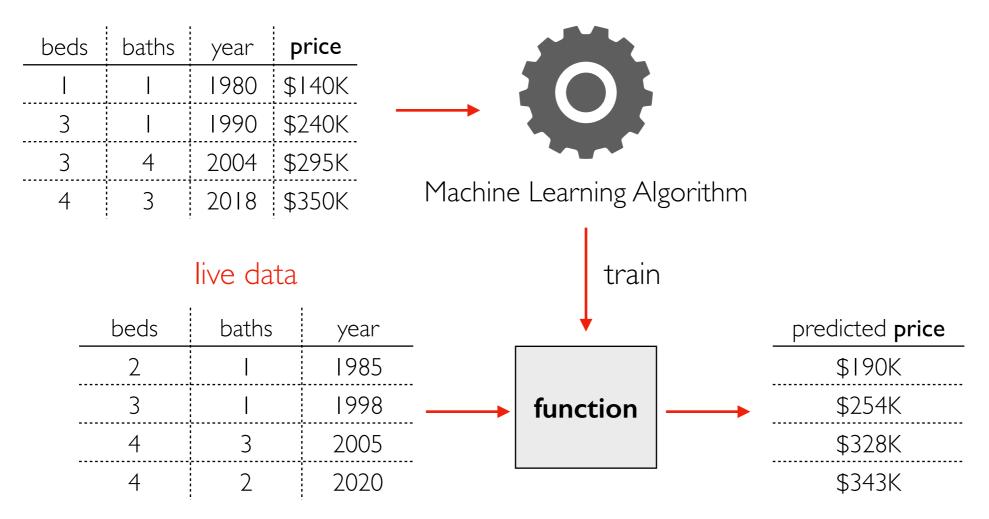




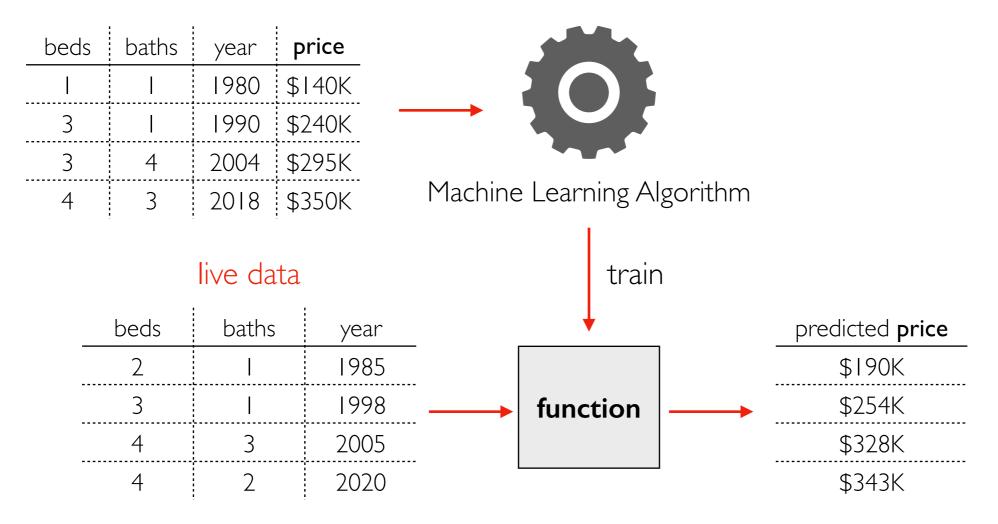




#### training data



#### training data

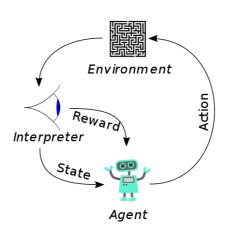


this is an example of a **regression** model, which in a type of **supervised machine learning**, which is one of the 3 main categories of ML

#### Machine Learning

Reinforcement Learning

not covered in CS 320



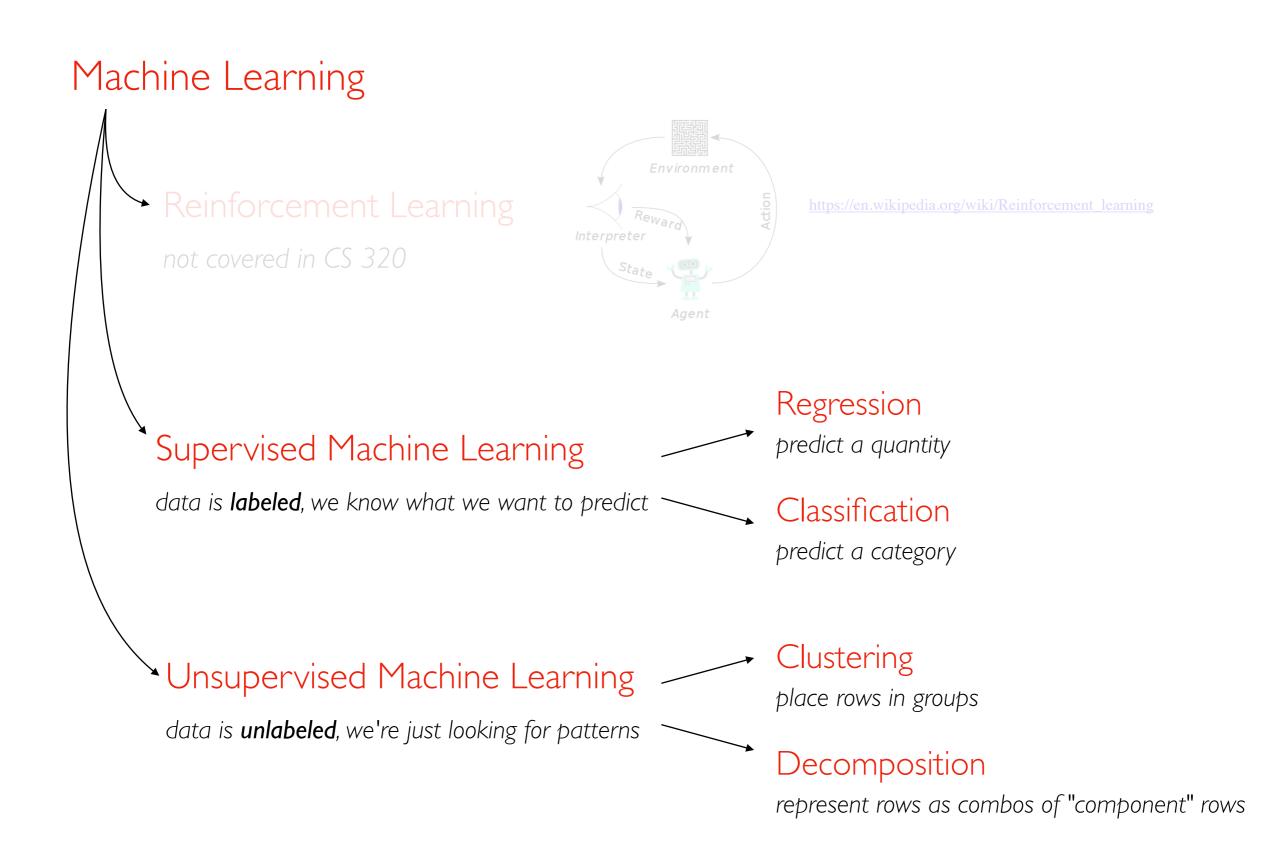
https://en.wikipedia.org/wiki/Reinforcement\_learning

#### Supervised Machine Learning

data is **labeled**, we know what we want to predict

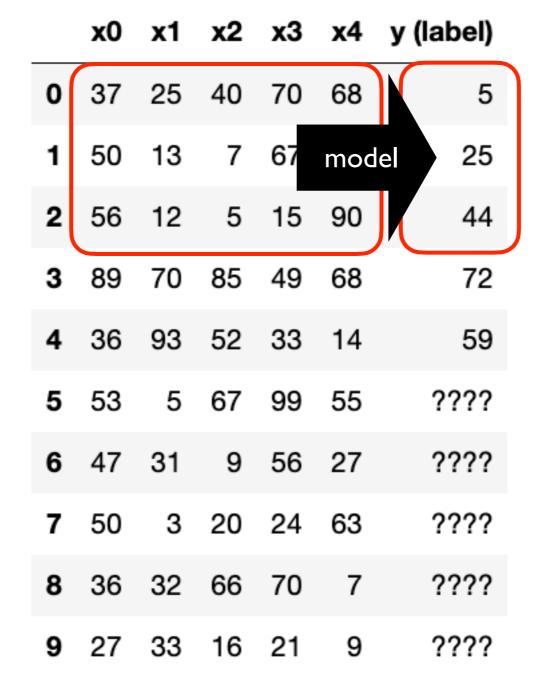
#### Unsupervised Machine Learning

data is **unlabeled**, we're just looking for patterns

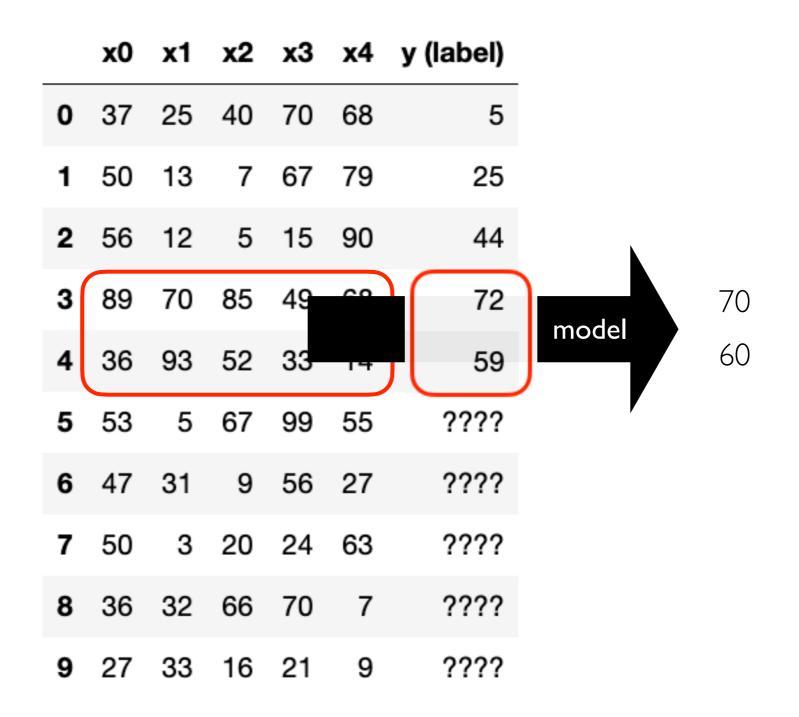


		fe	eature						
(	x0	<b>x1</b>	x2	х3	x4 y (label)				
0	37	25	40	70	68	5			
1	50	13	7	67	79	25			
2	56	12	5	15	90	44			
3	89	70	85	49	68	72			
4	36	93	52	33	14	59			
5	53	5	67	99	55	????			
6	47	31	9	56	27	????			
7	50	3	20	24	63	????			
8	36	32	66	70	7	????			
9	27	33	16	21	9	????			

problem: can we predict an unknown **quantity** based on **features**?



train: fit a model to the relationship between some label (y) and feature (x's) values



**test**: make some predictions for known rows -- how close are we?

	<b>x0</b>	<b>x1</b>	x2	х3	<b>x4</b>	y (label)
0	37	25	40	70	68	5
1	50	13	7	67	79	25
2	56	12	5	15	90	44
3	89	70	85	49	68	72
4	36	93	52	33	14	59
5	53	5	67	99	55	????
6	47	31	9	56	27	????
7	50	3	20	2	mode	????
8	36	32	66	70	7	????
9	27	33	16	21	9	????

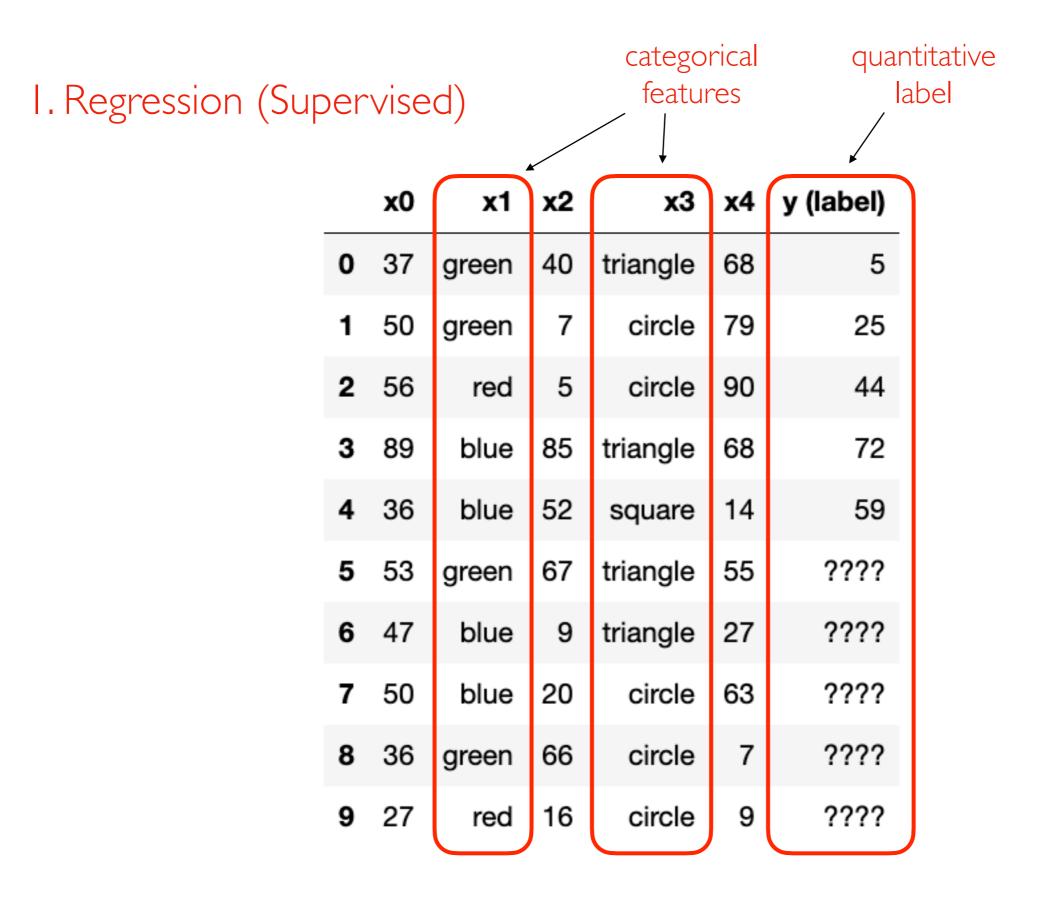
**production**: predict for actual unknowns

	<b>x0</b>	<b>x1</b>	x2	х3	<b>x4</b>	y (label)
0	37	25	40	70	68	5
1	50	13	7	67	79	25
2	56	12	5	15	90	44
3	89	70	85	49	68	72
4	36	93	52	33	14	59
5	53	5	67	99	55	90
6	47	31	9	56	27	85
7	50	3	20	2	mode	25
8	36	32	66	70	7	33
9	27	33	16	21	9	21

**production**: predict for actual unknowns

	<b>x0</b>	<b>x1</b>	x2	х3	<b>x4</b>	y (label)
0	37	25	40	70	68	5
1	50	13	7	67	79	25
2	56	12	5	15	90	44
3	89	70	85	49	68	72
4	36	93	52	33	14	59
5	53	5	67	99	55	90
6	47	31	9	56	27	85
7	50	3	20	24	63	25
8	36	32	66	70	7	33
9	27	33	16	21	9	21

#### **interpret**: what can we learn by looking directly at the model?



a problem with some **categorical** features is still a regression as long as the lable is **quantitative** 

#### 2. Classification (Supervised)

categorical label

	<b>x0</b>	x1	<b>x2</b>	x3	<b>x4</b>	y (label)
0	37	green	40	triangle	68	orange
1	50	green	7	circle	79	pear
2	56	red	5	circle	90	pear
3	89	blue	85	triangle	68	apple
4	36	blue	52	square	14	pear
5	53	green	67	triangle	55	????
6	47	blue	9	triangle	27	????
7	50	blue	20	circle	63	????
8	36	green	66	circle	7	????
9	27	red	16	circle	9	????

problem: can we predict an unknown **category**?

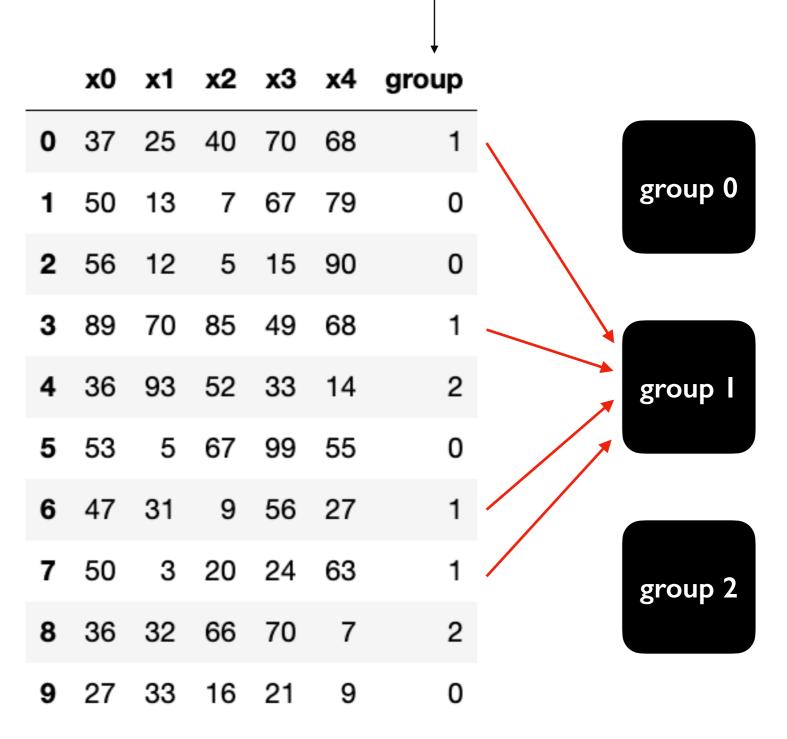
no label!

	x0	x1	x2	x3	x4
0	37	25	40	70	68
1	50	13	7	67	79
2	56	12	5	15	90
3	89	70	85	49	68
4	36	93	52	33	14
5	53	5	67	99	55
6	47	31	9	56	27
7	50	3	20	24	63
8	36	32	66	70	7
9	27	33	16	21	9

problem: can we organize data into groups of similar rows?

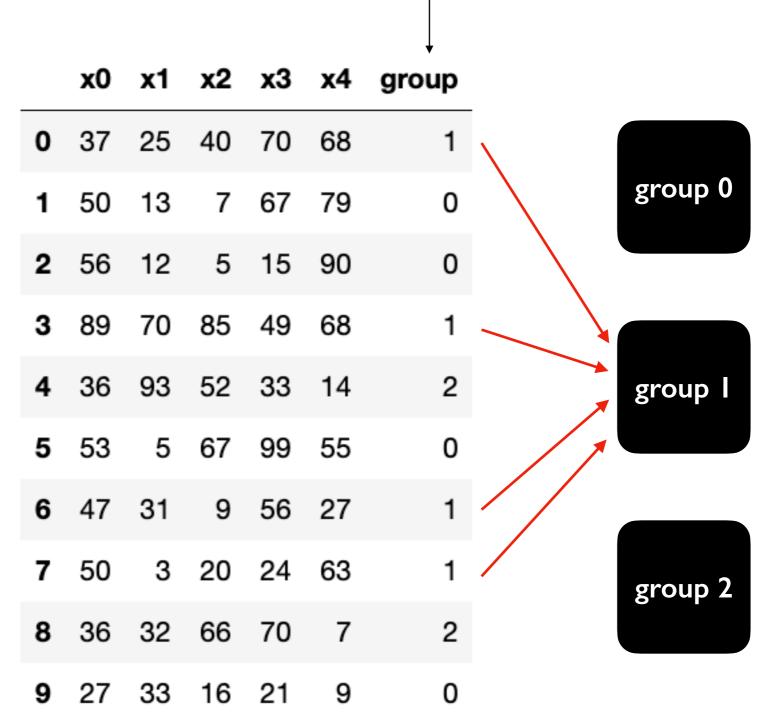
the algorithm decides groups

						+
	<b>x0</b>	<b>x1</b>	x2	х3	<b>x4</b>	group
0	37	25	40	70	68	1
1	50	13	7	67	79	0
2	56	12	5	15	90	0
3	89	70	85	49	68	1
4	36	93	52	33	14	2
5	53	5	67	99	55	0
6	47	31	9	56	27	1
7	50	3	20	24	63	1
8	36	32	66	70	7	2
9	27	33	16	21	9	0



the algorithm

decides groups



the algorithm

decides groups

there is no official grouping to check the model against, but a good grouping places similar rows together

	<b>x0</b>	<b>x1</b>	x2	х3	x4
0	-11	-7	3	20	20
1	2	-19	-30	17	31
2	8	-20	-32	-35	42
3	41	38	48	-1	20
4	-12	61	15	-17	-34
5	5	-27	30	49	7
6	-1	-1	-28	6	-21
7	2	-29	-17	-26	15
8	-12	0	29	20	-41
9	-21	1	-21	-29	-39

#### original data

#### components

	x0	<b>x1</b>	x2	x3	x4	-11		x0	<b>x1</b>	x2	х3	x4
0	-11	-7	3	20	20		0	-0.0	0.6	0.5	0.1	-0.6
1	2	-19	-30	17	31	21	1	0.3	-0.2	0.5	0.6	0.5
2	8	-20	-32	-35	42	-8	2	0.4	0.5	0.1	-0.6	0.5
3	41	38	48	-1	20							
4	-12	61	15	-17	-34							
5	5	-27	30	49	7							
6	-1	-1	-28	6	-21							
7	2	-29	-17	-26	15							
8	-12	0	29	20	-41							
9	-21	1	-21	-29	-39							

#### x1 x2 xЗ x2 x3 х0 x4 х0 x1 x4 -11 -0.0 0.6 0.5 0 0.1 -0.6 3 20 **0** -11 20 -7 21 31 0.3 -0.2 0.5 0.6 0.5 2 -19 -30 1 17 -8 2 0.4 0.5 0.1 -0.6 8 -20 -32 -35 0.5 42 41 38 48 -1 20 **4** -12 61 15 -17 -34 weights 5 -27 30 49 7

		pco	per	μυΖ
$\left( \right)$	0	-11	21	-8
	1	-43	12	-6
	2	-58	-14	30
	3	36	41	53
		00	0.0	0.0

nc1

nc2

original data

-1 -1 -28

2 -29 -17 -26

6 -21

0 29 20 -41

1 -21 -29 -39

15

1

2

3

5

6

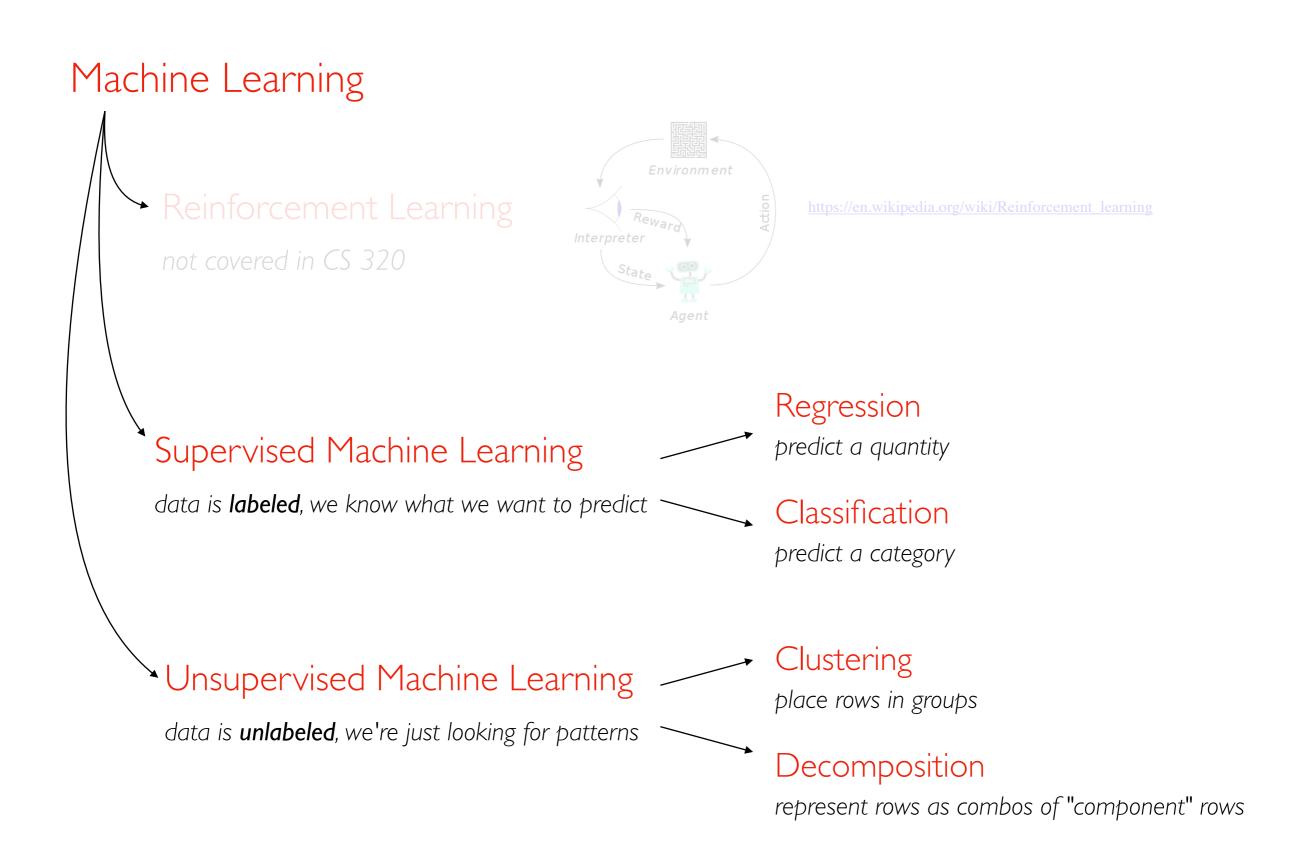
7

**8** -12

9 -21

components

		origii	nal da	ta					cor	npone	ents	
	x0	x1	x2	x3	x4			x0	x1	x2	х3	x4
0	-11	-7	3	20	20	-43	0	-0.0	0.6	0.5	0.1	-0.6
1	2	-19	-30	17	31	12	1	0.3	-0.2	0.5	0.6	0.5
2	8	-20	-32	-35	42	-6	2	0.4	0.5	0.1	-0.6	0.5
3	41	38	48	-1	20							
4	-12	61	15	-17	-34				$\bigvee$	eights		
5	5	-27	30	49	7				pc0	pc1	pc2	
6	-1	-1	-28	6	-21			0	-11	21	-8	
7	2	-29	-17	-26	15			1	-43	12	-6	
8	-12	0	29	20	-41			2	-58	-14	30	
9	-21	1	-21	-29	-39			3	36	41	53	



this semester, we'll learn one technique in each of these four categories

# I. Regression (Supervised) + 2. Classification (Supervised)

linear\_model.LogisticRegression([penalty, ...])
linear\_model.LogisticRegressionCV(\*[, Cs, ...])
linear\_model.PassiveAggressiveClassifier(\*)
linear\_model.Perceptron(\*[, penalty, alpha, ...])
linear\_model.RidgeClassifier([alpha, ...])
linear\_model.RidgeClassifierCV([alphas, ...])
linear\_model.SGDClassifier([loss, penalty, ...])

linear\_model.LinearRegression(\*[, ...])
linear\_model.Ridge([alpha, fit\_intercept, ...])
linear\_model.RidgeCV([alphas, ...])
linear\_model.SGDRegressor([loss, penalty, ...])

svm.LinearSVC([penalty, loss, dual, tol, C, ...])
svm.LinearSVR(\*[, epsilon, tol, C, loss, ...])

tree.DecisionTreeClassifier
tree.DecisionTreeRegressor
tree.ExtraTreeClassifier
tree.ExtraTreeRegressor

neighbors.KNeighborsClassifier([...])
neighbors.KNeighborsRegressor([n\_neighbors, ...])

#### 3. Clustering (Unsupervised)

cluster.AffinityPropagation(\*[, damping, ...])
cluster.AgglomerativeClustering([...])
cluster.Birch(\*[, threshold, ...])
cluster.DBSCAN([eps, min\_samples, metric, ...])
cluster.FeatureAgglomeration([n\_clusters, ...])
cluster.KMeans([n\_clusters, init, n\_init, ...])
cluster.MiniBatchKMeans([n\_clusters, init, ...])
cluster.MeanShift(\*[, bandwidth, seeds, ...])
cluster.OPTICS(\*[, min\_samples, max\_eps, ...])
cluster.SpectralClustering([n\_clusters, ...])
cluster.SpectralBiclustering([n\_clusters, ...])

#### 4. Decomposition (Unsupervised)

decomposition.DictionaryLearning([...])
decomposition.FactorAnalysis([n\_components, ...])
decomposition.FastICA([n\_components, ...])
decomposition.IncrementalPCA([n\_components, ...])
decomposition.KernelPCA([n\_components, ...])
decomposition.LatentDirichletAllocation([...])
decomposition.MiniBatchDictionaryLearning([...])
decomposition.NME([n\_components, init, ...])
decomposition.PCA([n\_components, copy, ...])
decomposition.SparsePCA([n\_components, ...])
decomposition.SparseCoder(dictionary, \*[, ...])
decomposition.TruncatedSVD([n\_components, ...])

scikit-learn machine learning modules: https://scikit-learn.org/stable/modules/classes.html

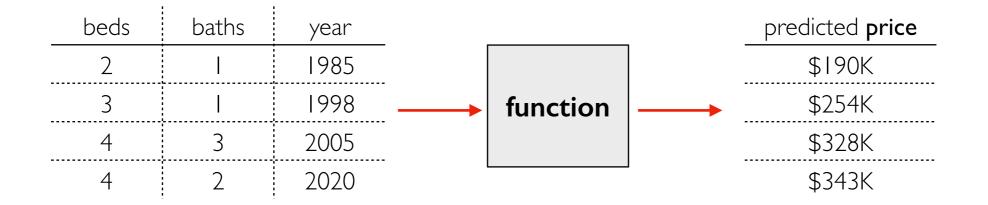
## Foundations: Modules and Math

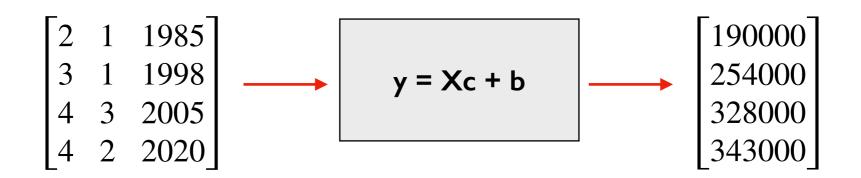
## Important Packages

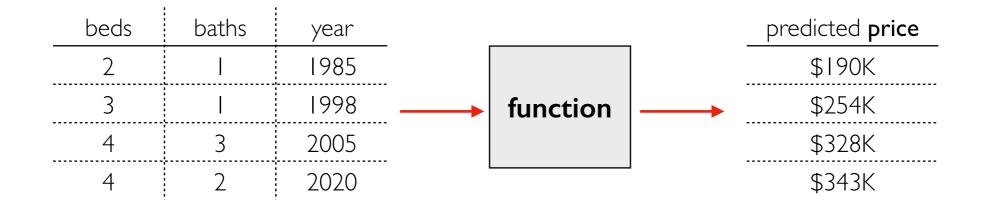
We'll be learning the following to do ML and related calculations efficiently:

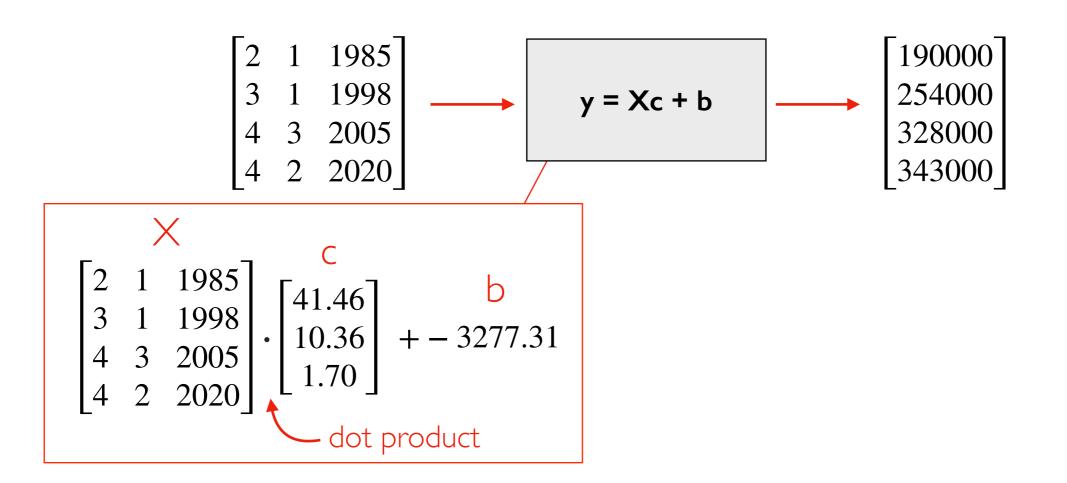


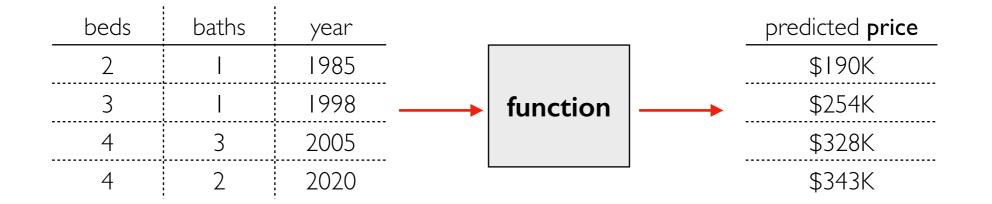
pip3 install numpy scikit-learn
pip3 install torch==1.4.0+cpu torchvision==0.5.0+cpu -f https://download.pytorch.org/whl/torch\_stable.html

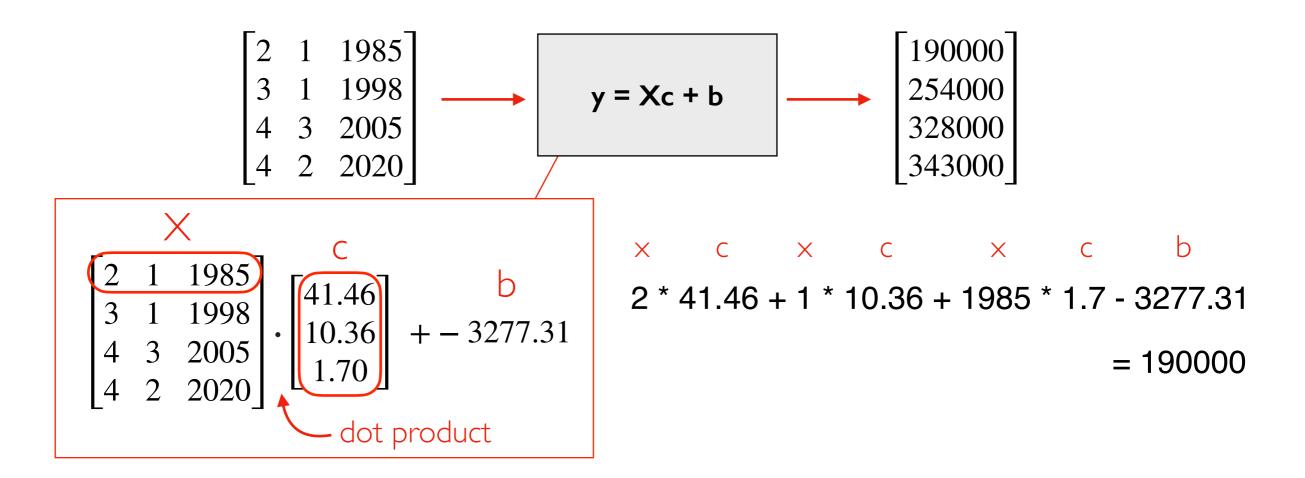


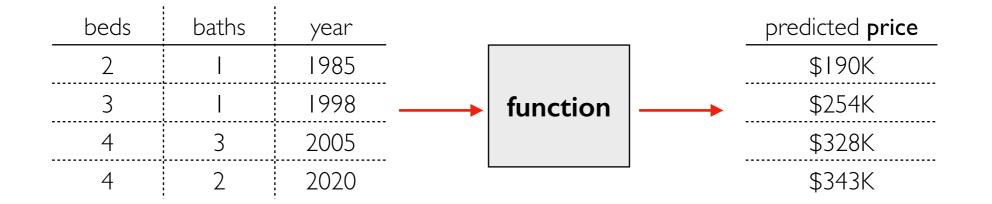


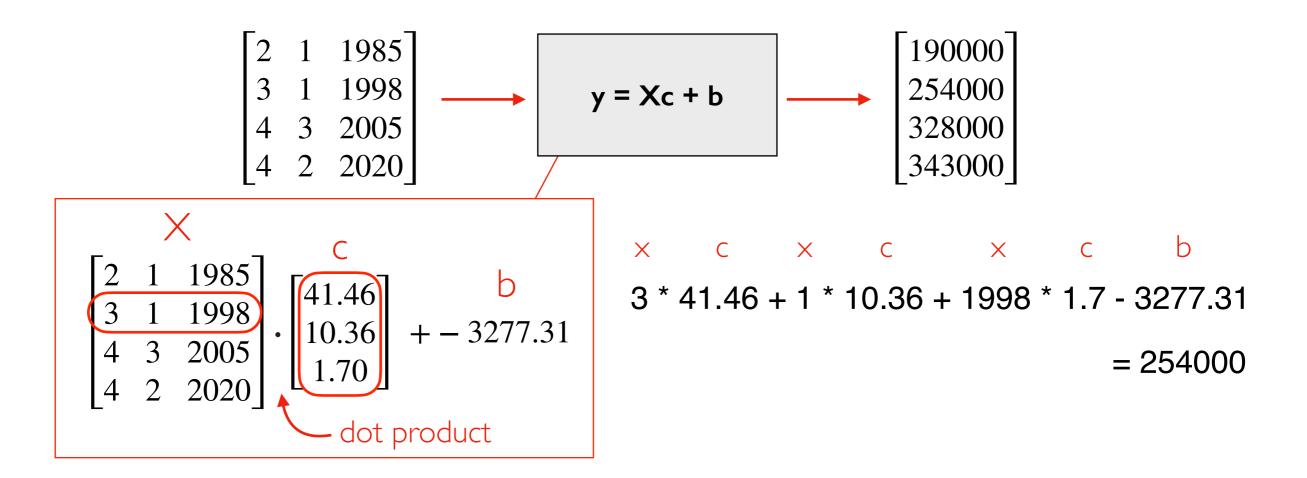


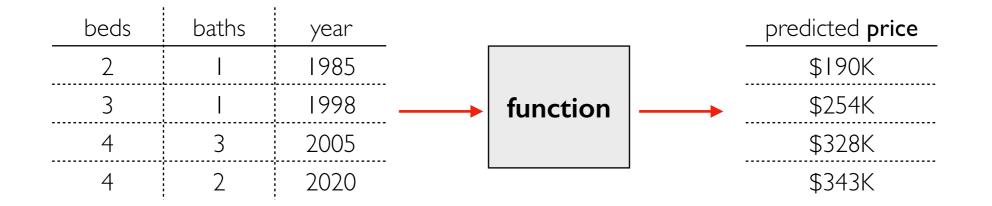


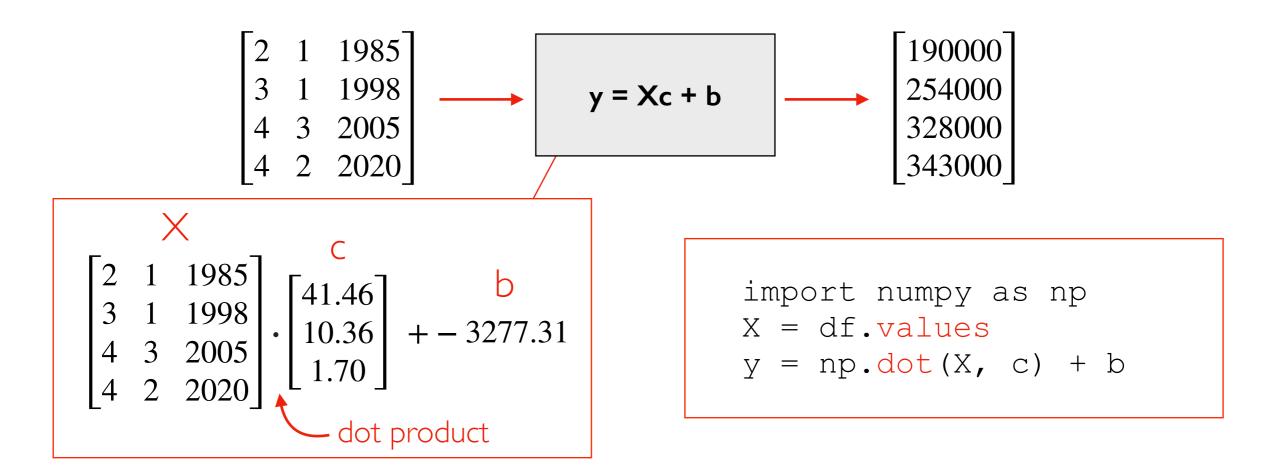


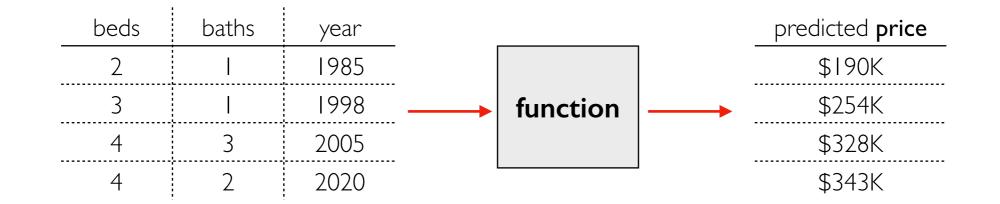


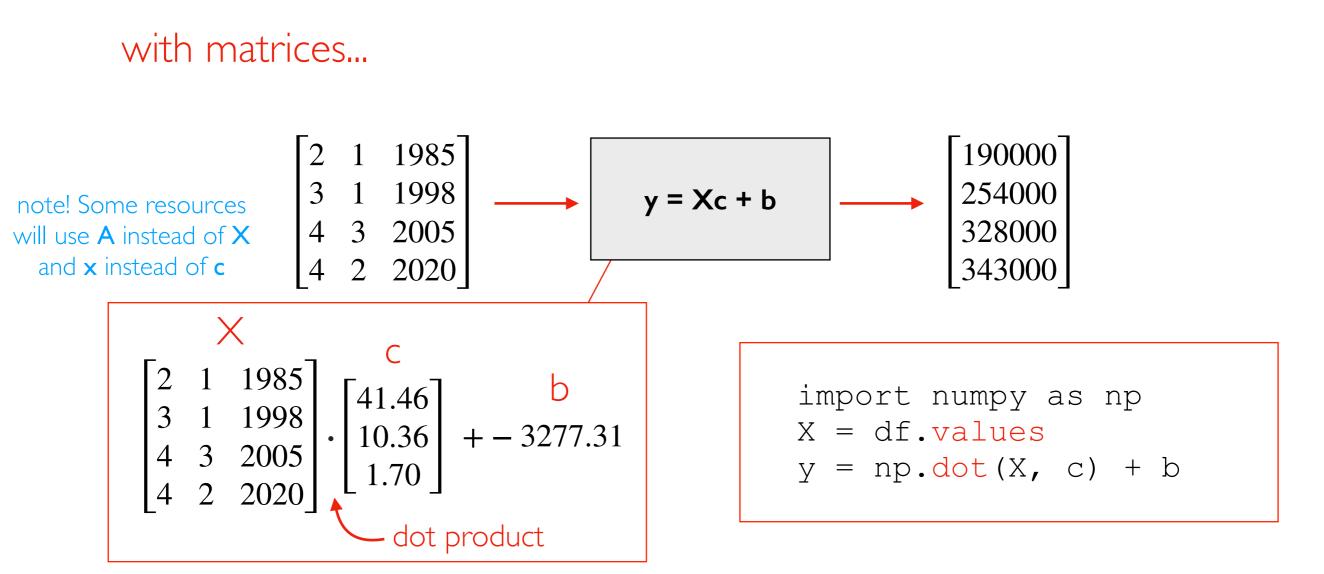




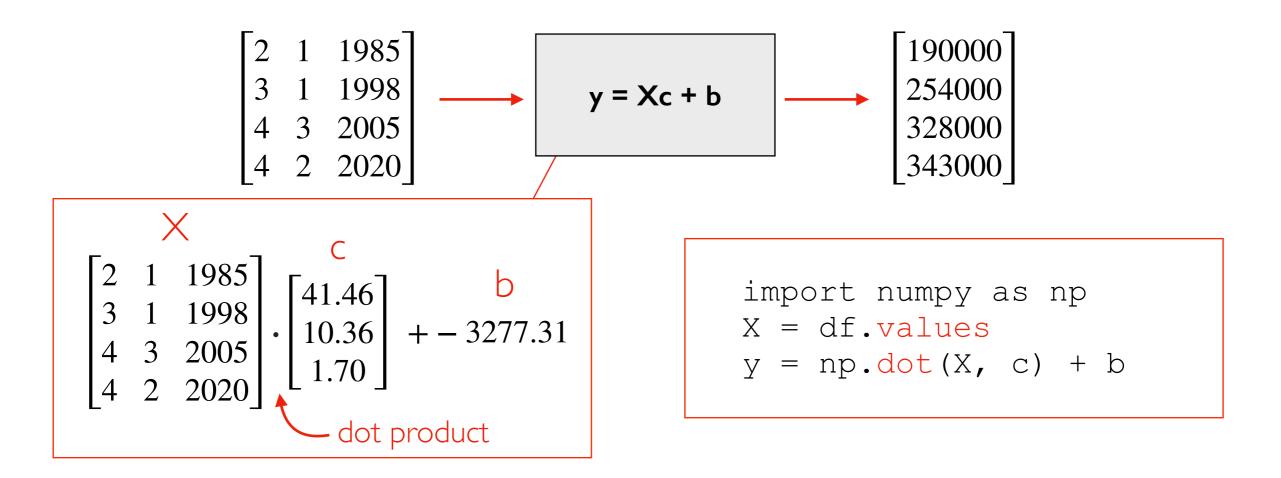








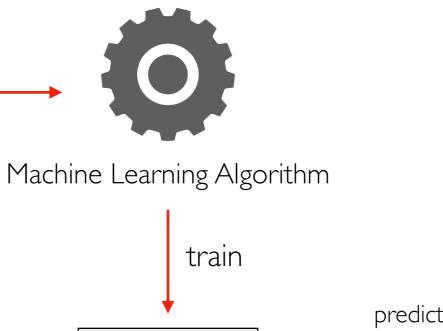
y = x \*\* 2 not linear y = 3\*c0 + -2\*c1 + 0.5\*c2 + ... + 10\*c49 linear

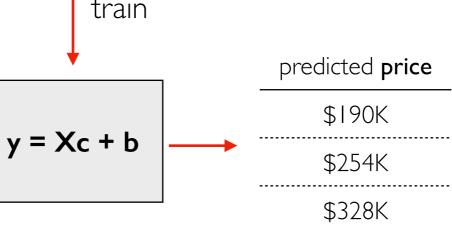


## Calculus

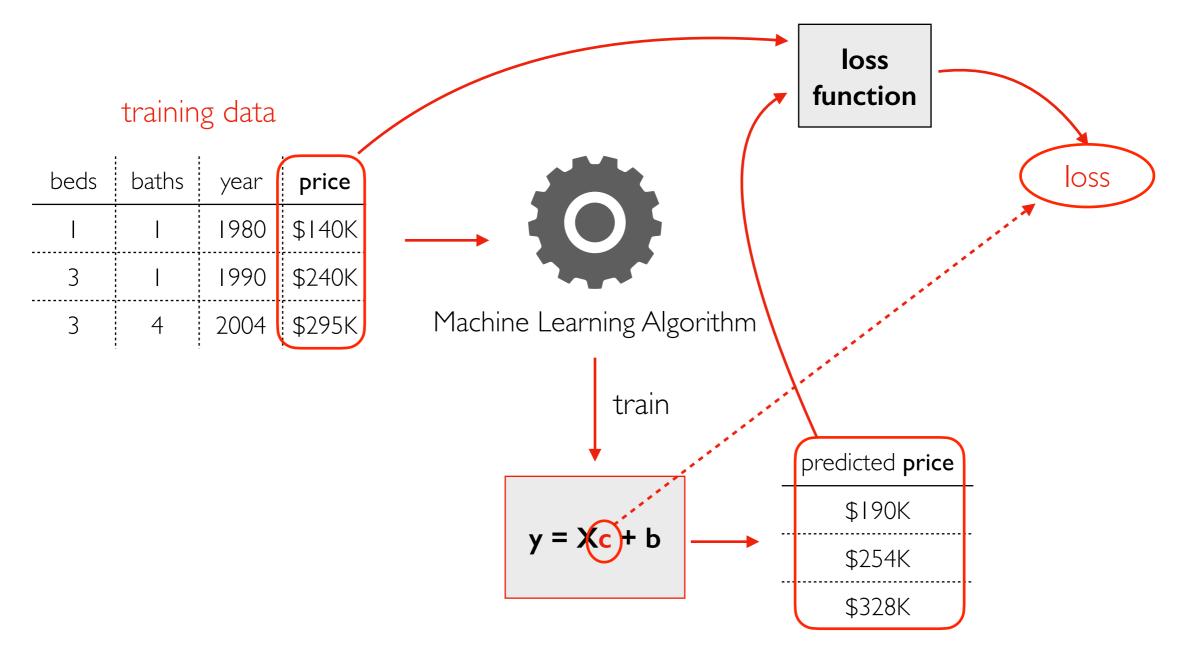
#### training data

beds	baths	year	price
I	l	1980	\$140K
3	l	1990	\$240K
3	4	2004	\$295K





## Calculus



how do we optimize **c** to minimize **loss**? Important concepts: derivative, gradient

## Parallelism

#### Parallelism

- doing multiple things at the same time
- requires multiple cores

#### GPUs (graphics processing units)

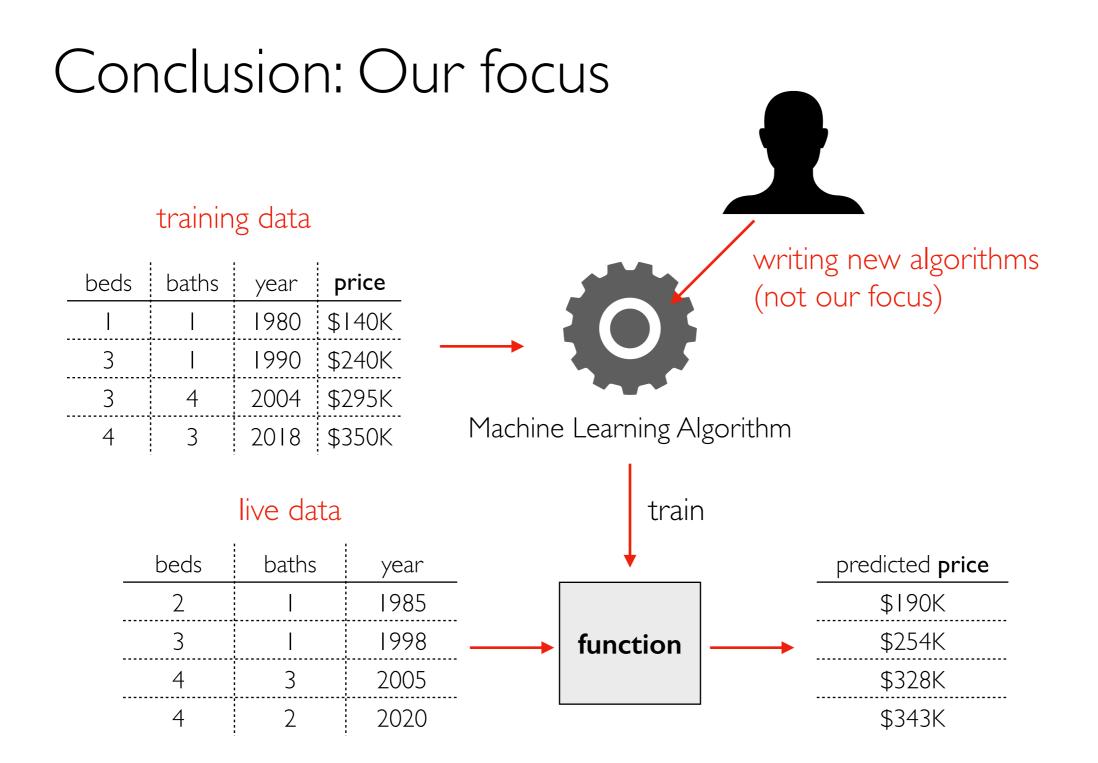
- graphics involves many of the same operation
- better to have many weaker cores working at once than fewer faster cores
- modern GPUs may have 1000s of cores (in contrast to 10s for CPUs)

#### Scientific Computing

- GPUs can greatly speed up key ML operations
  - multiplying matrices
  - computing gradients
- We'll learn pytorch for this...



## Conclusion: Developers vs. Users



## Conclusion: Our focus

how can we clean this up?

