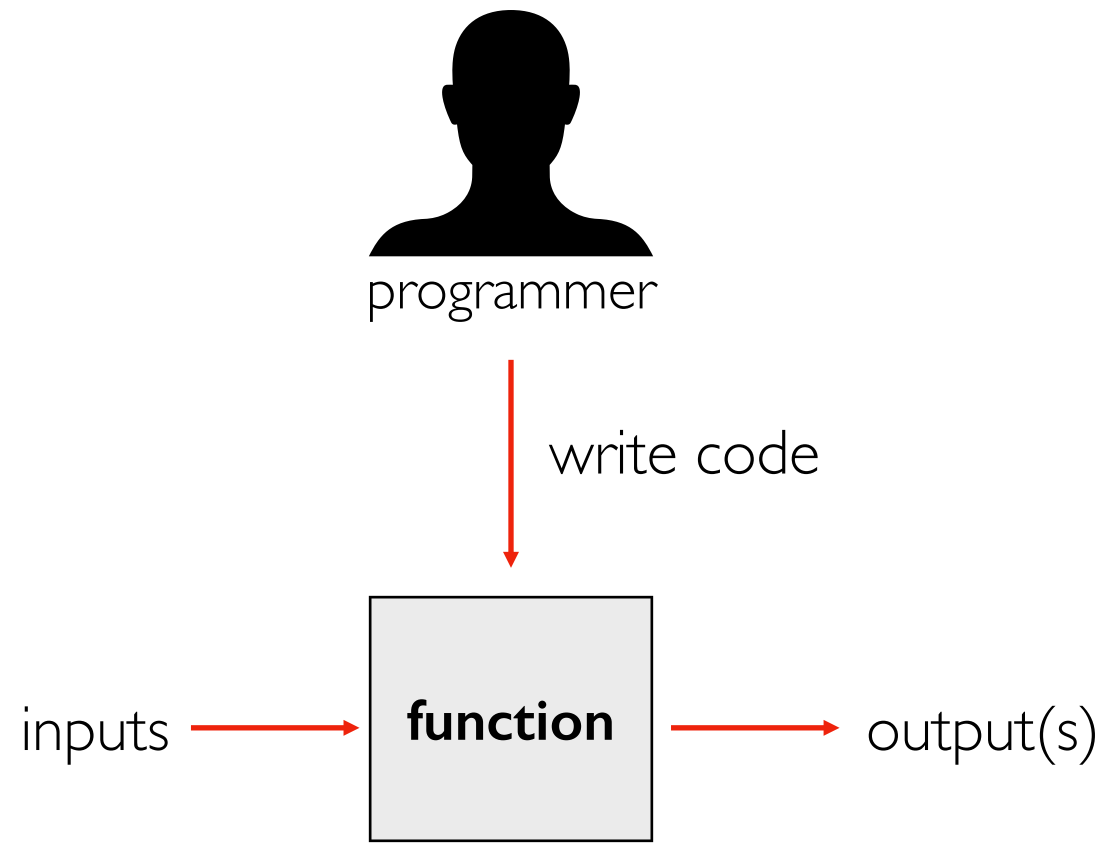
[320] Machine Learning: Intro

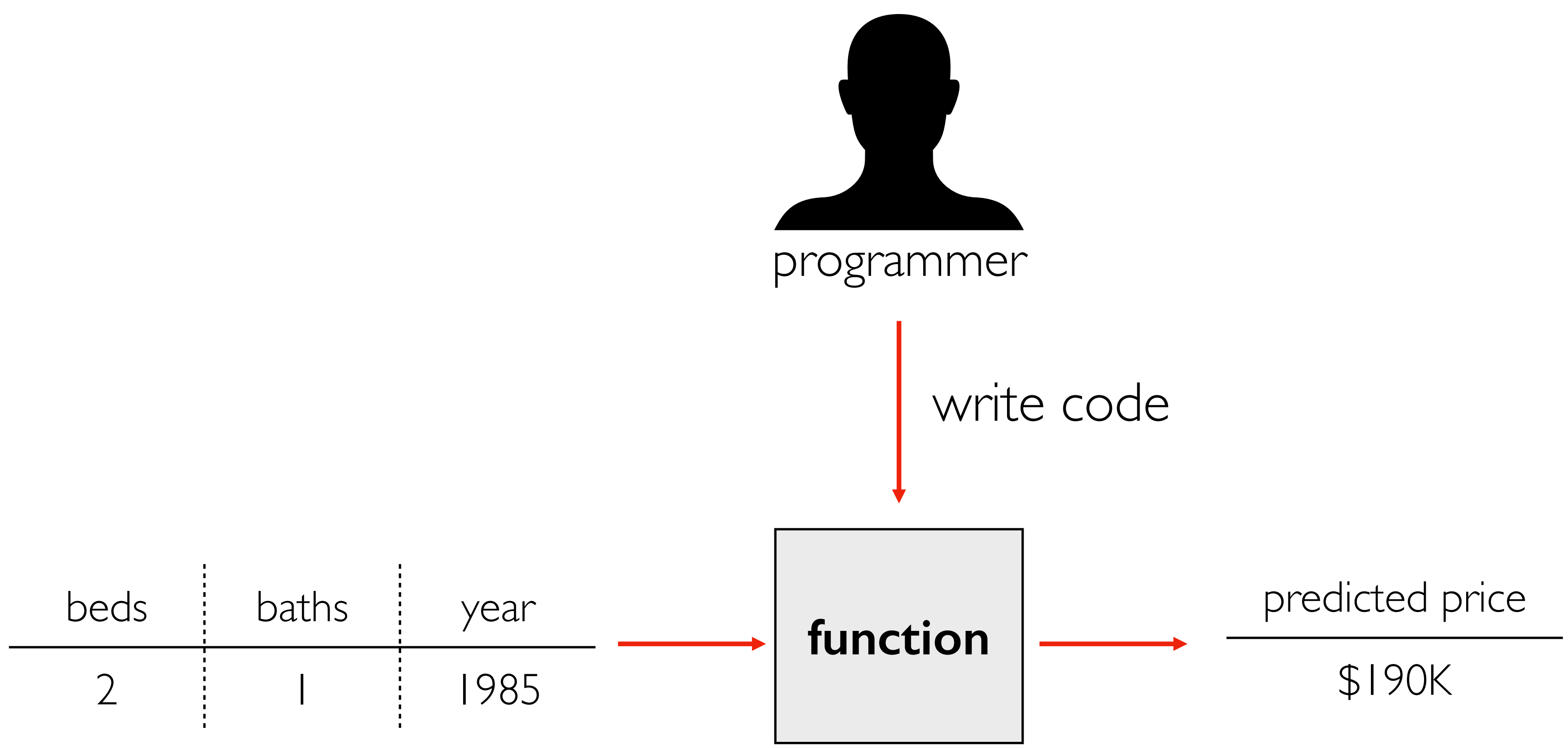
Meenakshi Syamkumar

Functions/Models

How do we make functions?

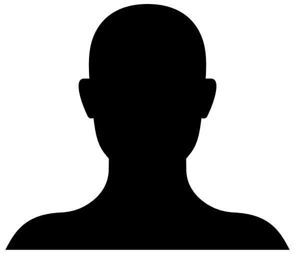


How do we make functions?



many functions are **models** that can be used to predict

How do we make functions?



programmer

write code

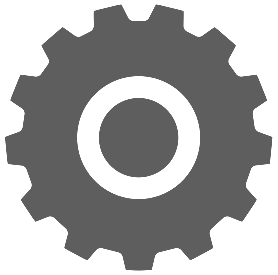
beds	baths	year
2	1	1985
3	1	1998
4	3	2005
4	2	2020

function

predicted price
$190K
$254K
$328K
$343K

many functions are **models** that can be used to predict

How do we make functions?



Machine Learning Algorithm

train

beds	baths	year
2	1	1985
3	1	1998
4	3	2005
4	2	2020

function

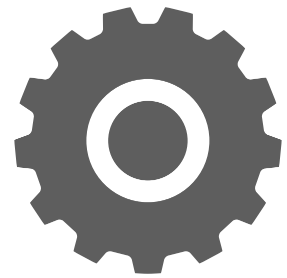
predicted **price**
$190K
$254K
$328K
$343K

many functions are **models** that can be used to predict

How do we make functions?

training data

beds	baths	year	**price**
1	1	1980	$140K
3	1	1990	$240K
3	4	2004	$295K
4	3	2018	$350K



Machine Learning Algorithm

train

live data

beds	baths	year
2	1	1985
3	1	1998
4	3	2005
4	2	2020

function

predicted **price**
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$254K
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many functions are **models** that can be used to predict

How do we make functions?

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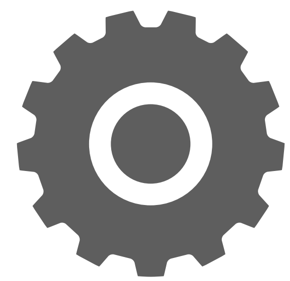

Machine Learning Algorithm

train

live data

beds	baths	year
2	1	1985
3	1	1998
4	3	2005
4	2	2020

function

predicted **price**
$190K
$254K
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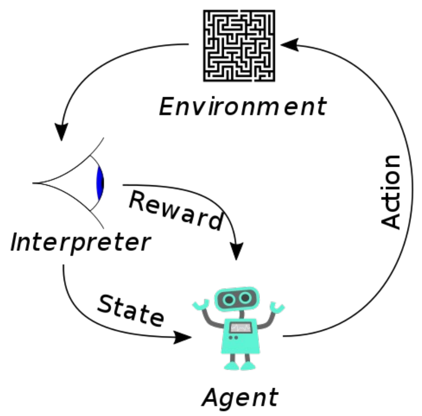
this is an example of a **regression** model, which in a type of **supervised machine learning**, which is one of the 3 main categories of ML

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

Machine Learning

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Supervised Machine Learning

data is labeled, we know what we want to predict

Regression

predict a quantity

Classification

predict a category

Unsupervised Machine Learning

data is unlabeled, we're just looking for patterns

Clustering

place rows in groups

Decomposition

represent rows as combos of "component" rows

1. Regression (Supervised)

features

	x0	x1	x2	x3	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**?

1. Regression (Supervised)

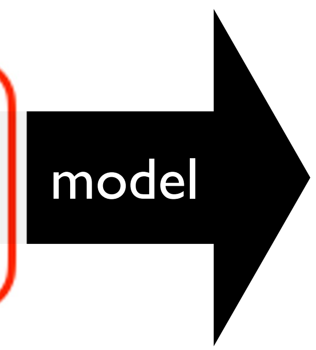
	x0	x1	x2	x3	x4	y (label)
0	37	25	40	70	68	5
1	50	13	7	67	[illegible]	25
2	56	12	5	15	90	44
3	89	70	85	49	68	72
4	36	93	52	33	14	59
5	53	5	67	99	55	????
6	47	31	9	56	27	????
7	50	3	20	24	63	????
8	36	32	66	70	7	????
9	27	33	16	21	9	????

model

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

1. Regression (Supervised)

	x0	x1	x2	x3	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	[redacted]	72
4	36	93	52	33	[redacted]	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	????



70

60

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

1. Regression (Supervised)

	x0	x1	x2	x3	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	2[illegible]	[illegible]	????
8	36	32	66	70	7	????
9	27	33	16	21	9	????

model

predict: estimate for actual unknowns

1. Regression (Supervised)

	x0	x1	x2	x3	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	90
6	47	31	9	56	27	85
7	50	3	20	2[illegible]	[illegible]	25
8	36	32	66	70	7	33
9	27	33	16	21	9	21

model

predict: estimate for actual unknowns

1. Regression (Supervised)

	x0	x1	x2	x3	x4	y (label)
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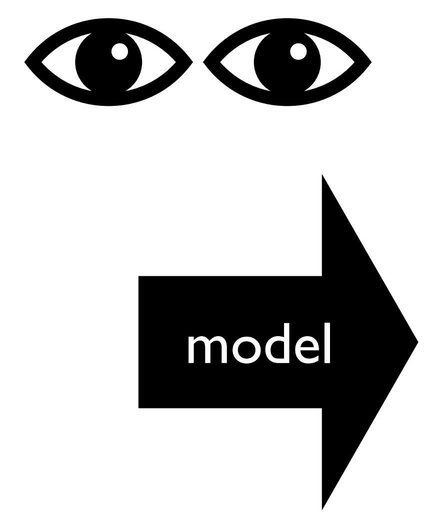
1	50	13	7	67	79	25
2	56	12	5	15	90	44
3	89	70	85	49	68	72
4	36	93	52	33	14	59
5	53	5	67	99	55	90
6	47	31	9	56	27	85
7	50	3	20	24	63	25
8	36	32	66	70	7	33
9	27	33	16	21	9	21



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

1. Regression (Supervised)

categorical features

quantitative label

	x0	x1	x2	x3	x4	y (label)
0	37	green	40	triangle	68	5
1	50	green	7	circle	79	25
2	56	red	5	circle	90	44
3	89	blue	85	triangle	68	72
4	36	blue	52	square	14	59
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	????

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

2. Classification (Supervised)

categorical label

	x0	x1	x2	x3	x4	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!

3. Clustering (Unsupervised)

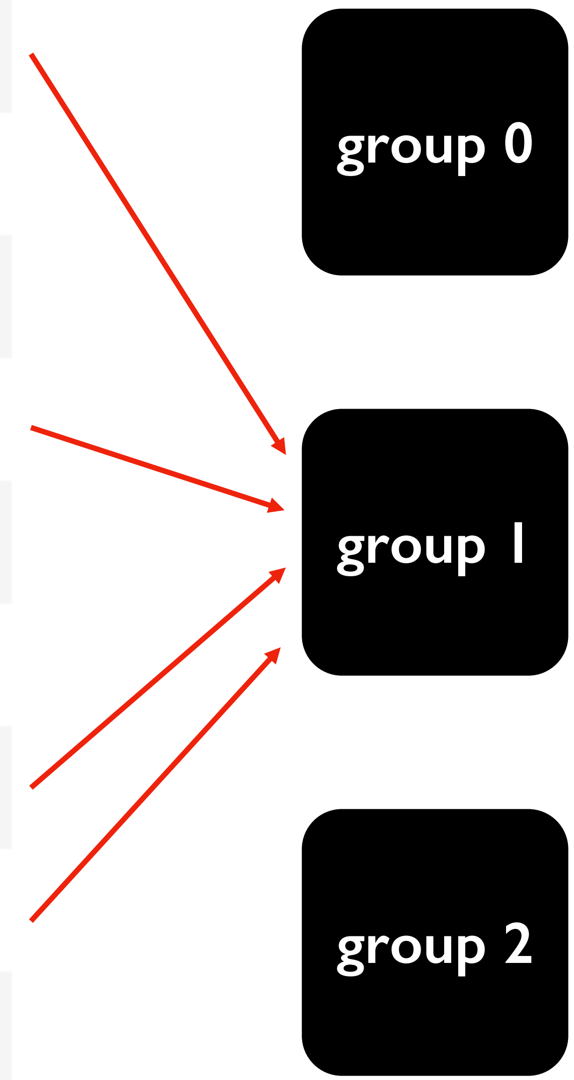
	x0	x1	x2	x3	x4
0	37	25	40	70	68
1	50	13	7	67	79
2	56	12	5	15	90
3	89	70	85	49	68
4	36	93	52	33	14
5	53	5	67	99	55
6	47	31	9	56	27
7	50	3	20	24	63
8	36	32	66	70	7
9	27	33	16	21	9

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

3. Clustering (Unsupervised)

the algorithm
decides groups

	x0	x1	x2	x3	x4	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



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

4. Decomposition (Unsupervised)

	x0	x1	x2	x3	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

4. Decomposition (Unsupervised)

original data

	x0	x1	x2	x3	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
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6	-1	-1	-28	6	-21
7	2	-29	-17	-26	15
8	-12	0	29	20	-41
9	-21	1	-21	-29	-39

-11

21

-8

components

	x0	x1	x2	x3	x4
0	-0.0	0.6	0.5	0.1	-0.6
1	0.3	-0.2	0.5	0.6	0.5
2	0.4	0.5	0.1	-0.6	0.5

4. Decomposition (Unsupervised)

original data

	x0	x1	x2	x3	x4
0	-11	-7	3	20	20
1	2	-19	-30	17	31
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-11

21

-8

components

	x0	x1	x2	x3	x4
0	-0.0	0.6	0.5	0.1	-0.6
1	0.3	-0.2	0.5	0.6	0.5
2	0.4	0.5	0.1	-0.6	0.5

weights

	pc0	pc1	pc2
0	-11	21	-8
1	-43	12	-6
2	-58	-14	30
3	36	41	53

...

4. Decomposition (Unsupervised)

original data

	x0	x1	x2	x3	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
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7	2	-29	-17	-26	15
8	-12	0	29	20	-41
9	-21	1	-21	-29	-39

-43

12

-6

components

	x0	x1	x2	x3	x4
0	-0.0	0.6	0.5	0.1	-0.6
1	0.3	-0.2	0.5	0.6	0.5
2	0.4	0.5	0.1	-0.6	0.5

weights

	pc0	pc1	pc2
0	-11	21	-8
1	-43	12	-6
2	-58	-14	30
3	36	41	53

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Machine Learning

Reinforcement Learning

not covered in CS 320

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data is labeled, we know what we want to predict

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predict a quantity

Classification

predict a category

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data is unlabeled, we're just looking for patterns

Clustering

place rows in groups

Decomposition

represent rows as combos of "component" rows

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

1. 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, ...])
```

classification!

```
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, ...])
cluster.SpectralCoclustering([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.MiniBatchSparsePCA([...])
decomposition.NMF([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:

1. numpy
2. pytorch
3. scikit-learn

```
pip3 install numpy scikit-learn

pip3 install torch torchvision
```

Linear Algebra

beds	baths	year
2	1	1985
3	1	1998
4	3	2005
4	2	2020

$\rightarrow$ **function** $\rightarrow$

predicted **price**
$190K
$254K
$328K
$343K

with matrices...

$$\begin{bmatrix} 2 & 1 & 1985 \\ 3 & 1 & 1998 \\ 4 & 3 & 2005 \\ 4 & 2 & 2020 \end{bmatrix} \rightarrow \boxed{\mathbf{y = Xc + b}} \rightarrow \begin{bmatrix} 190000 \\ 254000 \\ 328000 \\ 343000 \end{bmatrix}$$

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$$\underset{X}{\begin{bmatrix} 2 & 1 & 1985 \\ 3 & 1 & 1998 \\ 4 & 3 & 2005 \\ 4 & 2 & 2020 \end{bmatrix}} \cdot \underset{c}{\begin{bmatrix} 41.46 \\ 10.36 \\ 1.70 \end{bmatrix}} + \underset{b}{-3277.31}$$

dot product*

*dot product is usually between vectors by definition, but numpy uses np.dot for matrix multiplication

Linear Algebra

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dot product

$$\overset{x}{2} * \overset{c}{41.46} + \overset{x}{1} * \overset{c}{10.36} + \overset{x}{1985} * \overset{c}{1.7} - \overset{b}{3277.31}$$

$$= \underset{y}{190000}$$

Linear Algebra

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dot product

$$\overset{x}{3} * \overset{c}{41.46} + \overset{x}{1} * \overset{c}{10.36} + \overset{x}{1998} * \overset{c}{1.7} - \overset{b}{3277.31}$$

$$= \underset{y}{254000}$$

Linear Algebra

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note! Some resources will use **A** instead of **X** and **x** instead of **c**

$$\overset{X}{\begin{bmatrix} 2 & 1 & 1985 \\ 3 & 1 & 1998 \\ 4 & 3 & 2005 \\ 4 & 2 & 2020 \end{bmatrix}} \cdot \overset{c}{\begin{bmatrix} 41.46 \\ 10.36 \\ 1.70 \end{bmatrix}} + \overset{b}{-3277.31}$$

dot product

```
import numpy as np
X = df.values
y = np.dot(X, c) + b
```

Linear Algebra

```
y = x ** 2
```
not linear

```
y = x0*4 + x1*(-1) + x2*0.5 + ... + x10*3
```
linear

with matrices...

$$\begin{bmatrix} 2 & 1 & 1985 \\ 3 & 1 & 1998 \\ 4 & 3 & 2005 \\ 4 & 2 & 2020 \end{bmatrix} \longrightarrow \boxed{\mathbf{y = Xc + b}} \longrightarrow \begin{bmatrix} 190000 \\ 254000 \\ 328000 \\ 343000 \end{bmatrix}$$

$$\underbrace{\begin{bmatrix} 2 & 1 & 1985 \\ 3 & 1 & 1998 \\ 4 & 3 & 2005 \\ 4 & 2 & 2020 \end{bmatrix}}_{X} \cdot \underbrace{\begin{bmatrix} 41.46 \\ 10.36 \\ 1.70 \end{bmatrix}}_{c} + \underbrace{-3277.31}_{b}$$

dot product

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Calculus: Minimizing Something

training data

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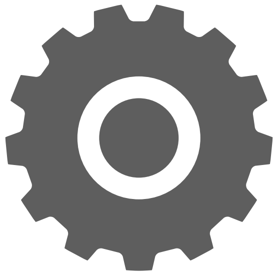

Machine Learning Algorithm

train

y = Xc + b

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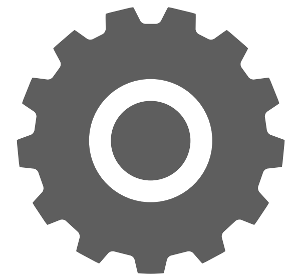

Machine Learning Algorithm

train

y = Xc + b

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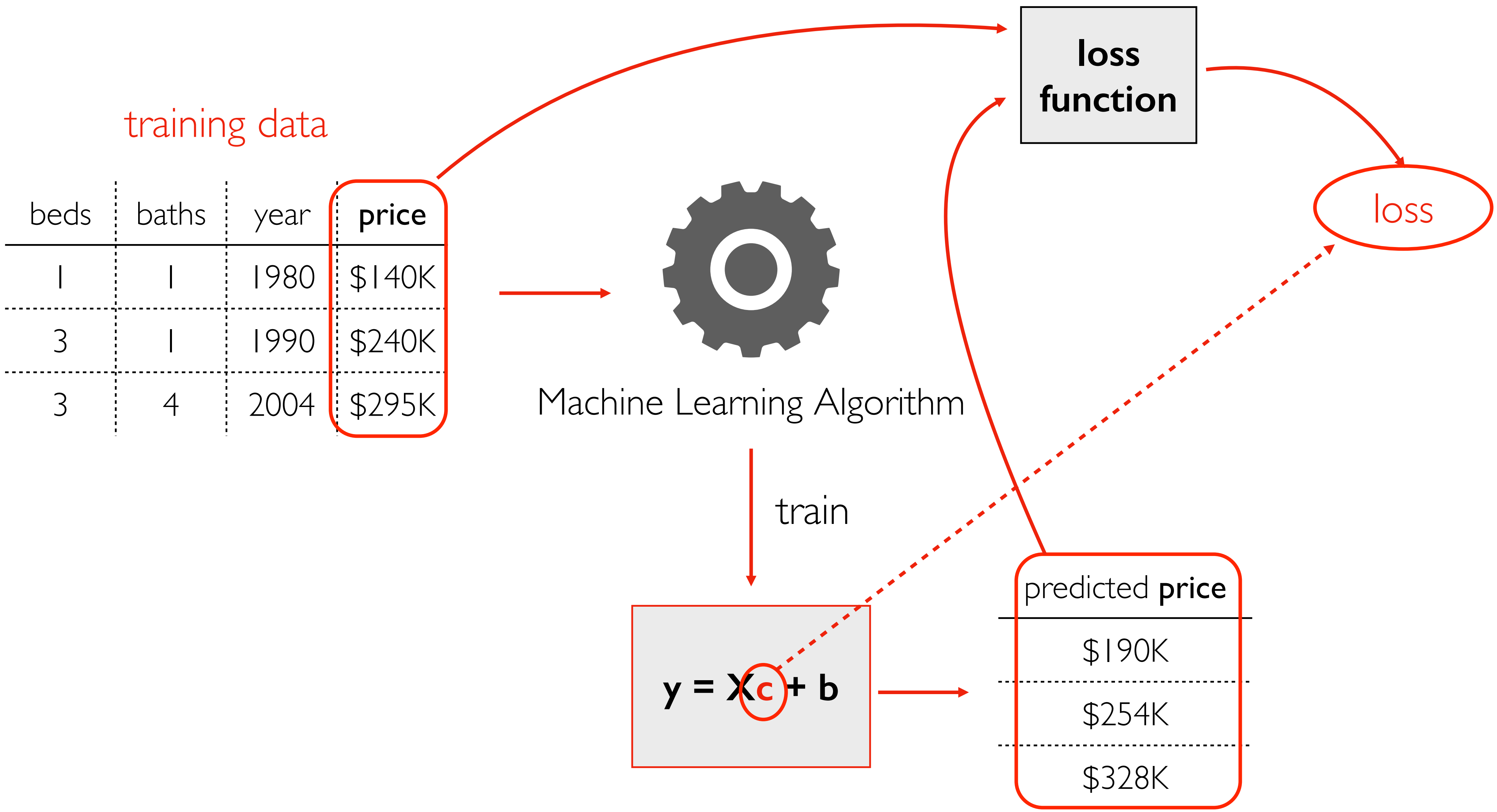
loss function

loss

how bad are the predictions?

Calculus: Minimizing Something



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1	1	1980	$140K
3	1	1990	$240K
3	4	2004	$295K

predicted **price**
$190K
$254K
$328K

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

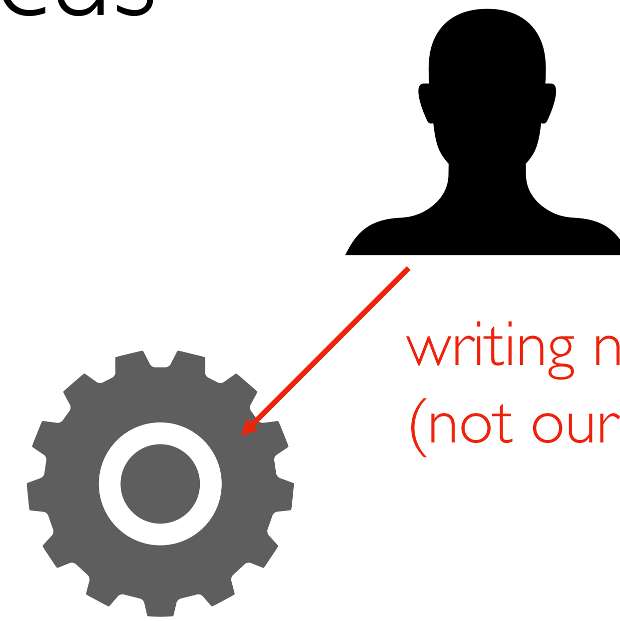
(pytorch can do this)

Conclusion: Developers vs. Users

Conclusion: Our Focus

training data

beds	baths	year	**price**
1	1	1980	$140K
3	1	1990	$240K
3	4	2004	$295K
4	3	2018	$350K



writing new algorithms
(not our focus)

Machine Learning Algorithm

train

live data

beds	baths	year
2	1	1985
3	1	1998
4	3	2005
4	2	2020

function

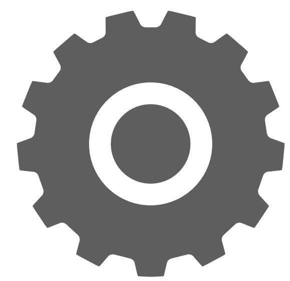
predicted **price**
$190K
$254K
$328K
$343K

Conclusion: Our Focus

how can we clean this up?

training data

beds	baths	year	**price**
1	1	1980	$140K
3	1	1990	$240K
3	4	2004	$295K
4	3	2018	$350K



Machine Learning Algorithm

which algorithm (from sklearn?) should we pick, and how should we configure it?

train

live data

beds	baths	year
2	1	1985
3	1	1998
4	3	2005
4	2	2020

function

is it working well? (evaluation)

predicted **price**
$190K
$254K
$328K
$343K