



Getting started with Machine Learning

Serverless Machine Learning with Cloud ML

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Notes:

2 hours lecture + 30 min of interactive quizzes interspersed + 30 min lab. Be smart about the timeline for this section. It will take the full 3 hours for an audience that is new to ML but should take less time if they already know some of this. Before you start diving into the slides, ask questions like:

- (1) Do you know what ML is?
- (2) Have you built a ML model before? What toolkit did you use?
- (3) Do you know what deep neural networks are?

Based on the answers to these questions, pace this material appropriately. For example, you should plan on covering this chapter in 60 minutes if the audience has prior experience with ML -- don't belabor the point and feel free to skip slides.

Agenda

What is Machine Learning?

Playing with ML

Effective ML

Creating ML datasets + Lab

Be smart about how deep to cover this section:

- (1) Normal pace
- (2) Cover only slides 6 and 17, using them to summarize the main points of section.
- (3) Skip this section completely.

Choose option #1 if these are developers new to ML. Choose #2 if these are enthusiasts who have read about ML already but have not built a ML model for their own use cases. Choose #3 if these are people who have used scikit-learn etc.

Machine Learning is a way to use standard algorithms to derive predictive insights from data and make repeated decisions



data



algorithm



predictive insight



decision

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ML is a way to derive *predictive* insights from data.

We do this using algorithms that are relatively general and applicable to a wide variety of datasets.

Think back to your company. How do you use data today? Perhaps you have a dashboard that business analysts and decision makers view on a daily basis? Perhaps a report that they read on a monthly basis? That is an example of backward-looking use of data -- looking at historical data to create reports and dashboards; that tends to be what people mean when they talk about business intelligence. A lot of data analytics is backwards-looking.

Of course, the point of looking at historical data might be to make decisions. Perhaps business analysts examine the data and suggest new policies or rules? They suggest, for example, that it might be possible to raise the price of a product in a certain region. Now, the business analyst is making a predictive insight. But is that scalable? Can the business analyst make such a decision for every product in every region? Can they dynamically adjust the price every second? In order to make decisions around predictive insights repeatable, you need machine learning. You need a computer program deriving such insights.

So, machine learning is about making many predictive decisions from data. It is about scaling up business intelligence and decision making.

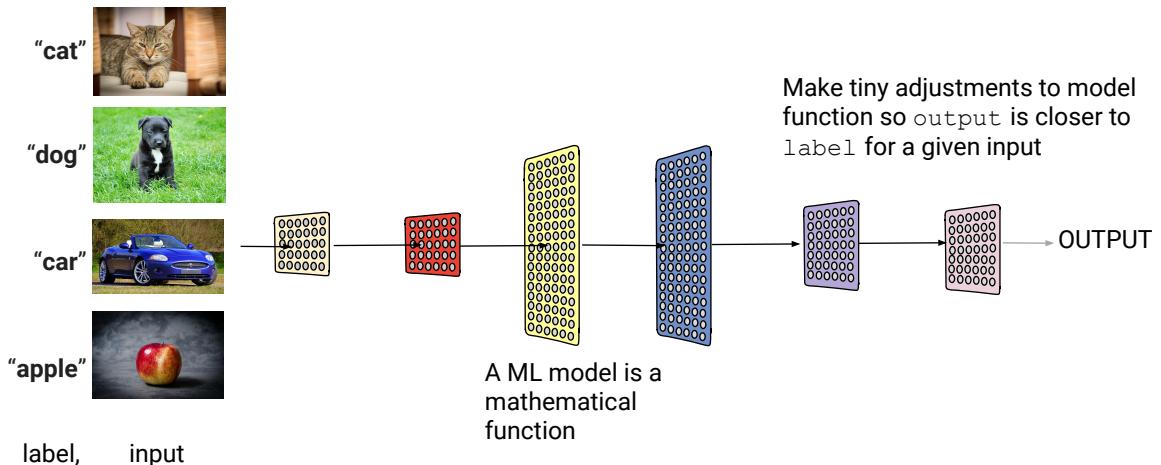
<https://pixabay.com/en/hard-disk-storage-computer-159264/> (cc0)

<https://pixabay.com/en/fractal-pattern-abstract-form-142748/> (cc0)

<https://pixabay.com/en/arrows-inside-pressure-request-2029157/> (cc0)

<https://pixabay.com/en/sign-direction-kids-cute-paint-2792576/> (cc0)

Stage 1: Train an ML model with examples



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The first stage of ML is to train an ML model with examples. The form of machine learning that we will be focused on in this specialization is called supervised learning, and in supervised learning, we start from examples.

An example consists of a label and an input. For example, suppose we want to train a machine learning model to look at images and identify what is in those images. The true answer is called the label, so "cat" for the first image and "dog" for the second image. The image itself, the pixels of the image, are the input to the model.

The model itself is a mathematical function, of a form that can be applied to a wide variety of problems.

The models used in ML have a bunch of adjustable parameters. Then when we "train" the model, what we do is to make tiny adjustments to the model so that the output of the model -- the output of the mathematical function -- is as close as possible to the true answer for a given input. Of course, we don't do this on one image at a time -- the idea is adjust the mathematical function so that overall, the outputs of the model for the set of training inputs is as close as possible to the training labels.

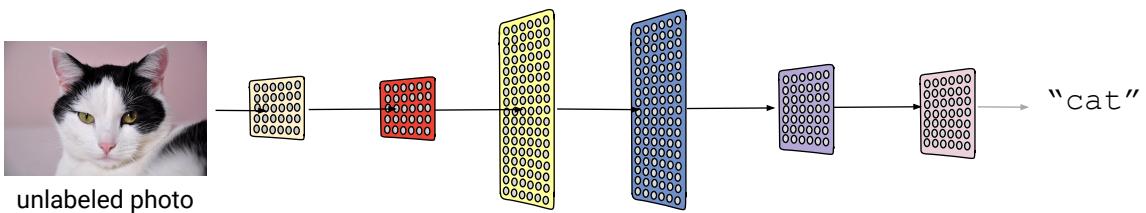
The key thing is that machine learning, at least ML of the form that we will consider in this course (the most mature form of ML), relies on having a dataset of labeled examples. Labeled examples -- input + the true answer.

<https://pixabay.com/en/dog-young-dog-puppy-280332/> (cc0)

<https://pixabay.com/en/sports-car-vehicle-transportation-1317645/> (cc0)

<https://pixabay.com/en/apple-education-school-knowledge-256268/> (cc0)

Stage 2: Predict with a trained model



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And after the model is trained, we can use it to “predict” the label of images that it has never seen before.

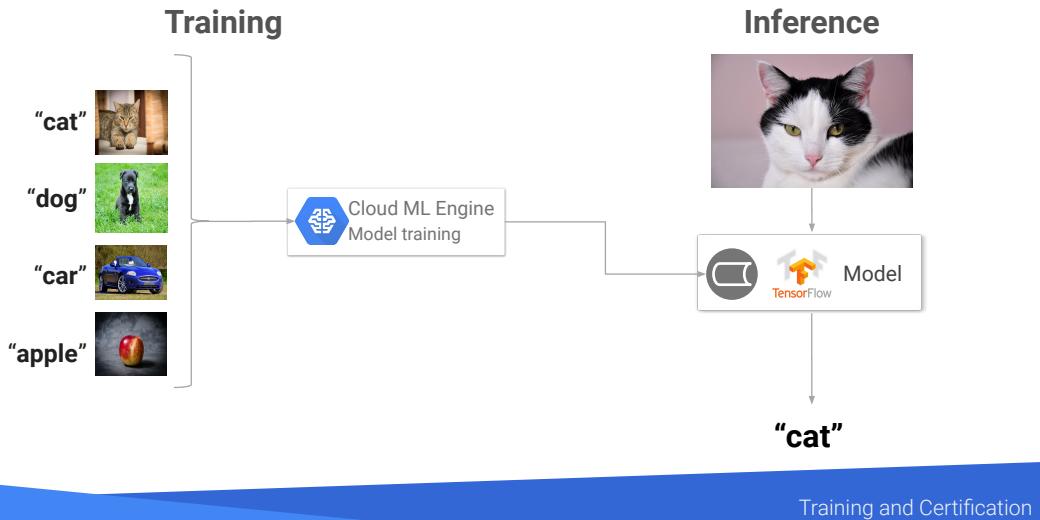
Here, we are inputting to the trained model this image and because the network has been trained, it is correctly able to output “cat”.

Note that the cat image on this slide is different from the one before it -- still works because the ML model has “generalized” from the specific examples of cat images we showed it to a more general idea of what a cat is and what it looks like.

The key to making a ML model generalize is data and lots and lots of it.
Having labeled data is a precondition for successful ML.

<https://pixabay.com/en/cats-a-normal-cat-pet-796437/> (cc0)

Data Engineers must focus on both the training and inference stages of ML



It is important to realize that machine learning has two stages: training and inference. Sometimes, people refer to “prediction” as “inference” because “prediction” seems to imply a future state and in the case of images like this, we are not really “predicting” that it is a cat, just “inferring” that it is a cat based on the pixel data.

It can be tempting, as a Data Engineer, to focus all your energy, on the first stage. But this is not enough.

You need to be able to operationalize the model, put the model into production so that you can run inferences.

Look at many books on machine learning, blog posts, university courses ... They tend to ignore this second stage of ML. But in the real-world, what is the use of training a ML model if you can not use it?

In this specialization, we will be careful to show you machine learning, end-to-end. And by end-to-end, we mean putting ML models into production.

[`https://pixabay.com/en/cat-cute-cat-baby-kitten-pet-1992140/\(cc0\)`](https://pixabay.com/en/cat-cute-cat-baby-kitten-pet-1992140/(cc0))

[`https://pixabay.com/en/mouse-rodent-cute-mammal-nager-1708347/`](https://pixabay.com/en/mouse-rodent-cute-mammal-nager-1708347/)

Do Now: In your own words, write down definitions for these ML terms

Term	Meaning
Label	
Input	
Example	
Model	
Training	
Prediction	

Notes:

Label = true answer

Input = predictor variable(s), what you can use to predict the label

Example = input + corresponding label

Model = math function that takes input variables and creates approximation to label

Training = adjusting model to minimize error

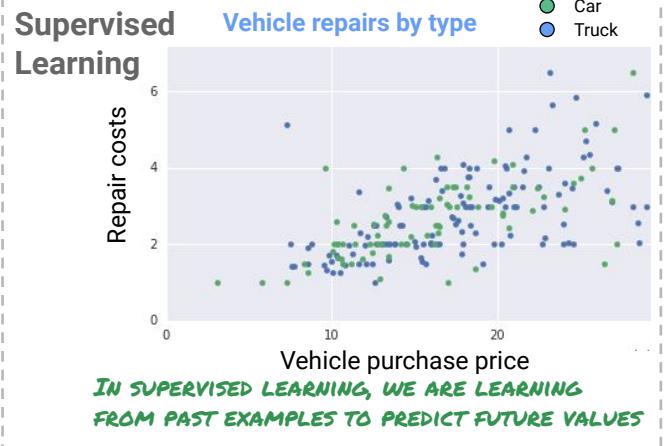
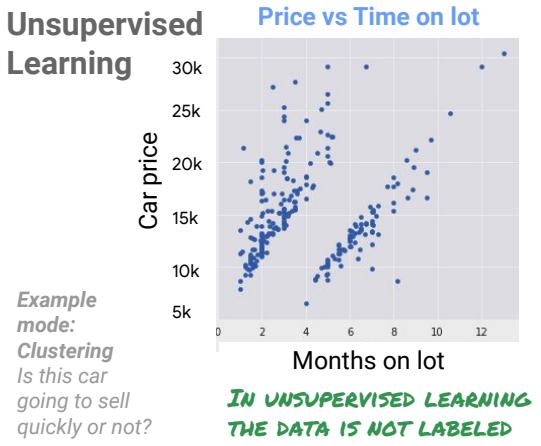
Prediction = using model on unlabeled data

Students are likely to struggle with the idea of a model. So, in the recap to this slide, delve more into models. So explain a ML model as a math function that weights & adds inputs and does mathematical transformations like tanh() to the numbers. And tell them that we will look at it again and again.

- That ML is a function can be hard for attendees to see. As an example, assume that the first layer returns the number of pixels that are brown/black/blue/red, and the second layer finds the most common color, and the third layer returns “cat” if previous layer had supplied “brown”. Based on just these images, that is a perfectly valid ML model. With more data, we’ll have to do more finely tuned ML functions.
- Now, if you know ml you are probably skeptical that my “function” above is really achievable with a neural network, so consider this.

- Mathematically, this model would be, for the first layer, [$\text{sum}(r = 255, g=255, b=255)$, ..., ..., $\text{sum}(r=255, g=0, b=0)$] -- this is just a set of appropriately positioned relu functions (okay, for $r=234$, we'd need two relu functions, so two layers, but you get the idea). The second layer would be a softmax layer. The third layer is simply an identity! [Instructors: don't go into this since it will only confuse a class ... if challenged, ask the person doing the challenging to read the slide notes.]

In supervised learning, you have labels



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Notes

Two of the most common classes of machine learning models are supervised and unsupervised ML models. The key difference is that with supervised models, we have labels, or in other words, the correct answers to whatever it is that we want to learn to predict.

In unsupervised learning, the data does not have labels.

The graph on the left is an example of the sort of problem that an unsupervised model might try to solve. You own a used car lot. Heye, you want to look at the months that a car remains on the lot and its price, and then group or cluster cars, to see whether a car is likely to sell quickly. Critically, there is no ground truth here; the car lot does not have one group of cars that it is trying to sell and another group of cars it plans to hold. Consequently, unsupervised problems are all about discovery, about looking at the raw data, and seeing if it naturally falls into groups. At first look, it seems that there are two distinct clusters or groups that could be separated nicely with a line.

In this course though, we'll be focused on supervised machine learning problems, like this one. The critical difference is that with supervised learning, we have some notion of a "label," or one characteristic of each data point that we care about a lot.

Typically, this is something we know about in historical data, but we don't know in real time. We know other things, which we call predictors, and we want to use those

predictors to predict the thing we don't know.

For example, let's say you are a purchaser for the used car lot. You have historical data on vehicle purchase prices for cars and trucks and how much was spent on repairs before the vehicle could be sold. Now you are at an auction. And you are looking at a vehicle that is for sale. You know the asking price and you know whether it is a car or a truck. But you don't know how much the repairs are going to be. In the historical data, the repair expense is a label. You create a model to predict the repair expense from the asking price. Then you try to predict the repairs, in real time, based on historical data and the values you know for a specific vehicle. This will give you an indicator of whether the asking price is a good deal for the vehicle or if they are asking too much because of the repair expenses. You will have an indicator how to bid at the auction.

<https://pixabay.com/illustrations/chevrolet-limousine-usa-pkw-2178828/>



Regression and classification are supervised ML model types

Price	Repairs	Type	Accident	Year	Odometer
43k	1,012	Truck	No	2012	53,232
6k	830	Car	No	2003	140,091
18k	2,704	Car	Yes	2017	6,508
3k	3,153	Truck	No	1999	162,000
35k	205	Car	No	2015	23,122

Model 1
Regression

Model 2
Classification

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Within supervised ML there are two types of problems: regression and classification. To explain them, let's dive a little deeper into this data.

In this dataset of repair expenses, each row has many characteristics, such as type of vehicle, whether it has been involved in an accident, the year it was manufactured, and the odometer reading indicating how far it has traveled. We'll choose one of the columns as the characteristic we want to predict, called the "label". And we choose a set of the other columns which are called the "features".

In new model 1, we want to predict the repair amount. Therefore, the column "Repairs" is my label. I can use one, all, or any number of the other columns as my features to predict the repairs.

This will be a regression model because repairs is a continuous label.

In new model 2, we want to predict the whether the vehicle has been in an accident. Once again, I will use some set of the rest of the columns as features and try to predict the accident field. This will be a classification model because the label has a discrete number of values or classes.

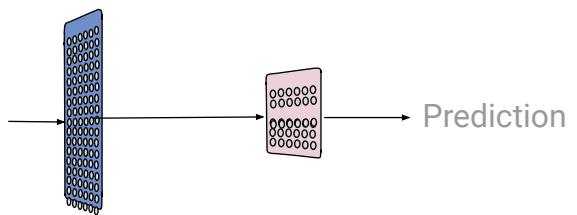
<https://pixabay.com/photos/pontiac-usa-wreck-dare-corrosion-2257344/>

A data warehouse can be a source of structured data training examples for your ML model

```
SELECT
  purchase_price,
  year_manufactured,
  accident_reported,
  dented_bumper,
  odometer_reading
FROM
  `bigquery-private-data.used.vehicles`
WHERE accident_reported is not null AND dented_bumper
```

Rate	Price	Repairs	Type	Accident	Year	Dented	Odometer
4.53	43k	1,012	Truck	No	2012	Front	53,232
23.7	6k	830	Car	No	2003	No	140,091
12.4	18k	2,704	Car	Yes	2017	No	6,508
6.35	3k	3,153	Truck	No	1999	Rear	162,000
33.67	35k	205	Car	No	2015	No	23,122

DATA ON VEHICLES IS SOURCED FROM THE COMPANY'S BIGQUERY DATA WAREHOUSE USING SQL



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Notes

Now, where does this data come from? The tips dataset is what we call structured data -- consisting of rows and columns -- and a very common source of structured data for machine learning is your data warehouse. Unstructured data is things like pictures, audio, or video.

Here I'm showing you a vehicle dataset, a private dataset of company information. It is a dataset in BigQuery that is in your data warehouse

Let's say we want to predict the Odometer reading of the vehicle. In other words, we want to predict how far the vehicle has been driven.

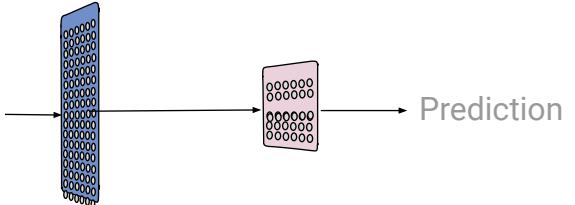
You can do a SQL SELECT statement in BigQuery to create a ML dataset -- we will choose input features to the model, things like purchase price, accidents reported, manufacturing year, and type of vehicle.

Because the Odometer reading is a continuous value, this is a regression problem.

Making predictions from structured data is very commonplace, and that is what we focus on in the first part of the specialization.

Since rate is a continuous value, use regression to predict

Rate	Price	Repairs	Type	Accident	Year	Dented	Odometer
4.53	43k	1,012	Truck	No	2012	Front	53,232
23.7	6k	830	Car	No	2003	No	140,091
12.4	18k	2,704	Car	Yes	2017	No	6,508
6.35	3k	3,153	Truck	No	1999	Rear	162,000
33.67	35k	205	Car	No	2015	No	23,122



FUEL EFFICIENCY (RATE) IS STORED AS A FLOATING POINT NUMBER, REPRESENTING A CONTINUOUS (REAL) VALUE

REGRESSION DNN MODEL

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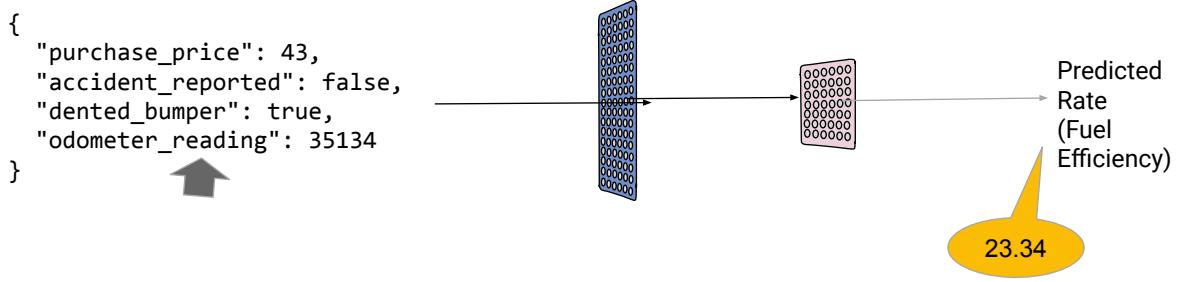
Of course, this dataset can be used to predict other things too.

Perhaps we want to predict fuel efficiency (such as kilometers per liter), the rate at which fuel is consumed. And we want to predict this using other attributes of the data as features.

Fuel efficiency can be an indicator of the condition of the internal components like the engine and the drive train. So this could be a very useful value to predict.

The label here would be Rate, and it is a continuous variable. It is stored as a floating point number, which would make this a regression problem.

The model is fed information collected in real-time, and used for prediction



The key point here is that you are predicting from real-time data, for example, from Cloud Pub/Sub or your web application.
This information might originate from an online car auction service.

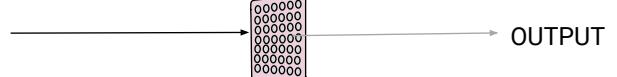
The model may even have only one layer



Rate	Price	Repairs	Type	Accident	Year	Dented	Odometer
4.53	4.3k	1,012	Truck	No	2012	Front	53,232
23.7	6k	830	Car	No	2003	No	140,091
12.4	18k	2,704	Car	Yes	2017	No	6,508
6.35	3k	3,153	Truck	No	1999	Rear	162,000
33.67	35k	205	Car	No	2015	No	23,122

rate =

$$\begin{aligned}
 & w_0 * \text{year_manufactured} \\
 & + w_1 * \text{accident_reported} \\
 & + w_2 * \text{bumper_dented} \\
 & + w_3 * \text{odometer_reading} \\
 & + b
 \end{aligned}$$



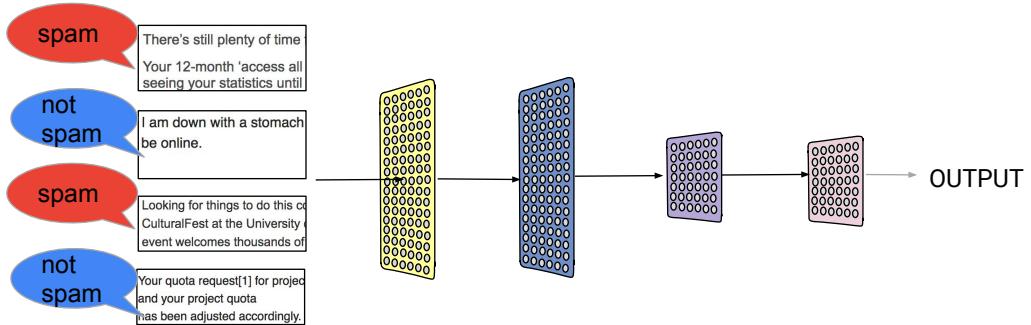
Notes:

Training involves finding weights w_0, w_1, w_2, w_3 such that the predicted rate (fuel_efficiency) is really, really close to the labels.

A neural network with no hidden layers is a linear model ...

- Point out that the model here is a lot simpler than the one on the previous slides – more layers in a DNN makes it more complex. Models on structured data are typically only a few layers deep whereas image classification DNNs can have hundreds of layers.

A classification model can be used to detect whether email is spam or not



The input here is text

Notes:

- Key words on this slide: “classification” -- use these words in a sentence.
- Say that is another classification problem, similar to the dog/cat/ example. In this case, we have only two categories or labels.
- The input here does not seem numeric ...

The inputs for unstructured data are still ultimately just numbers



N-dimensional array of pixel values

There's still plenty of time
Your 12-month 'access all
seeing your statistics until

Each word is mapped to a vector
e.g., "the" could be [0 4 5 0 3 4]
Coming up with an appropriate vector for a word
is itself a machine learning problem

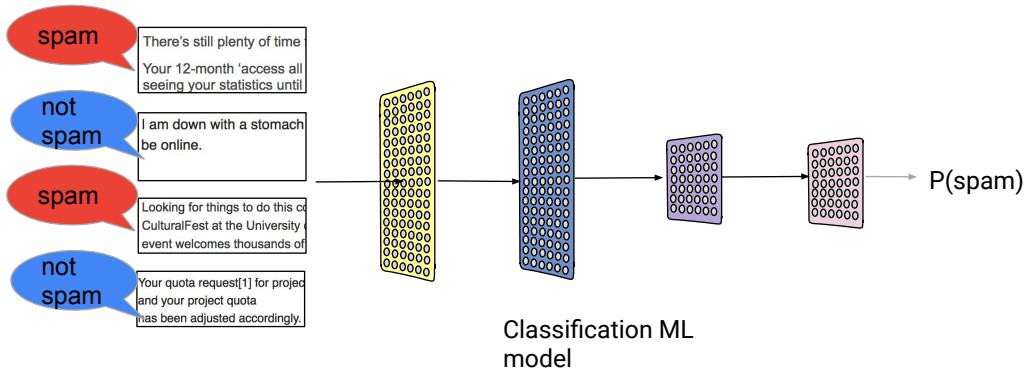
Notes:

Pixel values here are [r, g, b, a] and the image itself is 2D, so it could be a width x height x 4 array.

word2vec

<https://pixabay.com/en/rocket-launch-smoke-rocket-take-off-67723/> (cc0)

The output of the model might be the probability that the email is spam



Notes:

- Note the probabilistic output -- we would have to threshold the probability if we wanted "spam" or "not spam". The previous model returned a probability for each label (cat, dog, etc.) and we picked the most likely (usually, we also threshold; i.e., we don't return "cat" if the $P(\text{cat})$ is only 0.01).

Machine Learning used in lots of industries

Manufacturing

- Predictive maintenance or condition monitoring
- Warranty reserve estimation
- Propensity to buy
- Demand forecasting
- Process optimization
- Telematics

Retail

- Predictive inventory planning
- Recommendation engines
- Upsell and cross-channel marketing
- Market segmentation and targeting
- Customer ROI and lifetime value

Healthcare and Life Sciences

- Alerts and diagnostics from real-time patient data
- Disease identification and risk satisfaction
- Patient triage optimization
- Proactive health management
- Healthcare provider sentiment analysis

Travel and Hospitality

- Aircraft scheduling
- Dynamic pricing
- Social media—consumer feedback and interaction analysis
- Customer complaint resolution
- Traffic patterns and congestion management

Financial Services

- Risk analytics and regulation
- Customer Segmentation
- Cross-selling and upselling
- Sales and marketing campaign management
- Credit worthiness evaluation

Energy, Feedstock and Utilities

- Power usage analytics
- Seismic data processing
- Carbon emissions and trading
- Customer-specific pricing
- Smart grid management
- Energy demand and supply optimization

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Do Now: Pick 5 use cases from previous slide and fill out this table

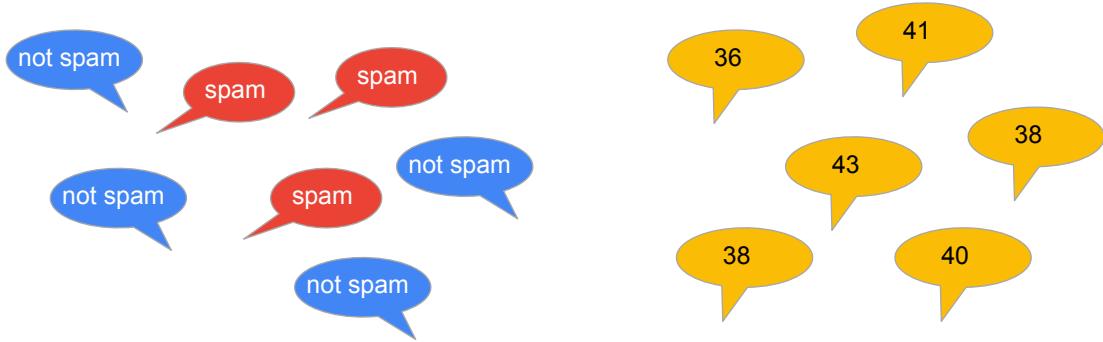
Use case	Label	Input(s)	Classification or regression?

Agenda

Playing with ML

This section should take 20-40 minutes based on audience. In my experience, even people who know ML get something out of this section because it introduces neural networks, deep networks, and feature engineering in an intuitive way. However, the more sophisticated the audience, the faster you should cover this.

Machine Learning is an approach to making many similar decisions based on data

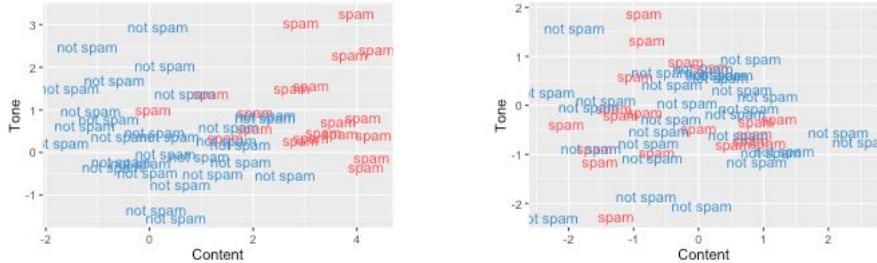


Notes:

You train the computer using lots of examples. On the left is spam-filtering. On the right, the gestation model.

This slide is here to make more obvious the relationship between the “real” examples in previous section and the “toy” example in this one.

ML = Pattern recognition from examples

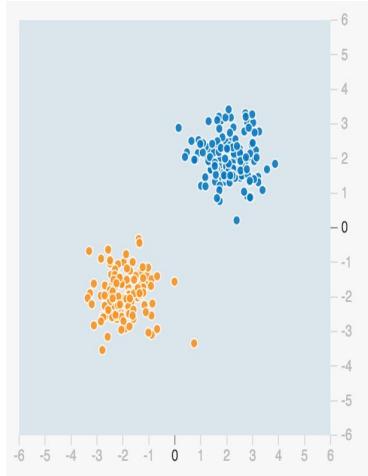


Notes:

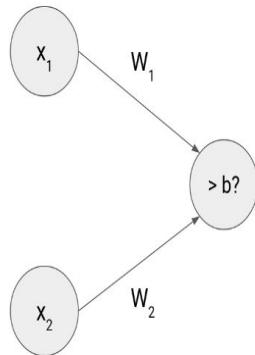
The right-hand side is a more difficult problem than the left-hand side, but with non-linear models and transformations, the ML model can usually manage to find a way to separate the two classes to varying levels of accuracy. Use the right-hand side to lead into a discussion on accuracy, which leads into next slide. Also, tie in the blue-red here to the dots on the next slide.

Graphs created by Cassie Kozyrkov, Google

How do you classify these points?



We could create a ML model consisting of a single neuron



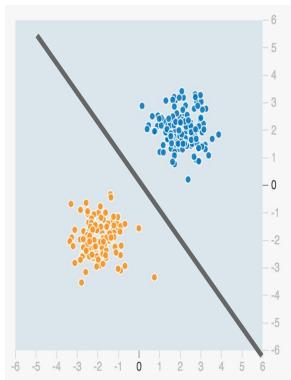
$$w_1x_1 + w_2x_2 > b$$

Graphically, that translates to: find a line
that separates the two sets of points

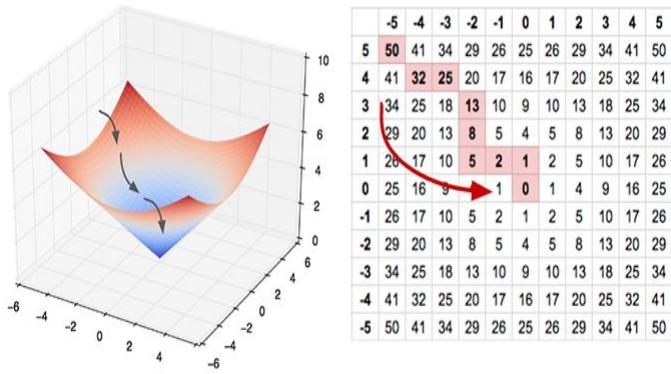
bias
(threshold)

$$w_1x_1 + w_2x_2 > b$$

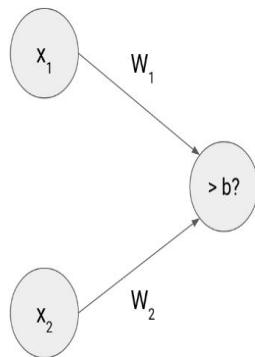
weights



Gradient descent is used to find the best parameters



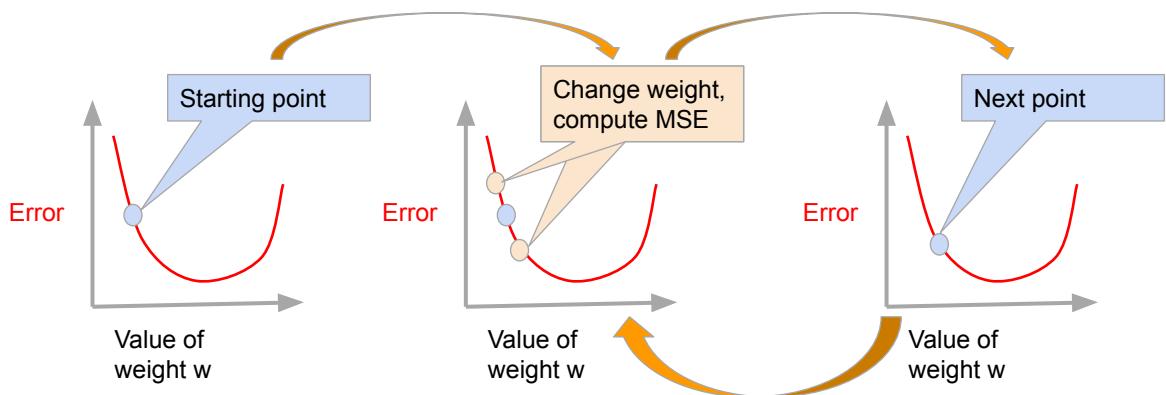
We can use gradient descent to find the best weights and bias



$$w_1x_1 + w_2x_2 > b$$

The computer tries to find the best **parameters**

Recompute error after each batch of examples (not full dataset)

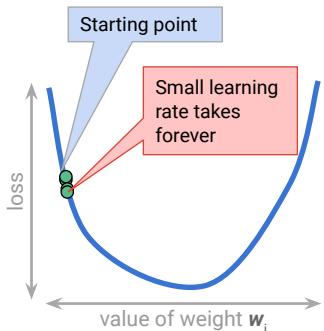


Notes:

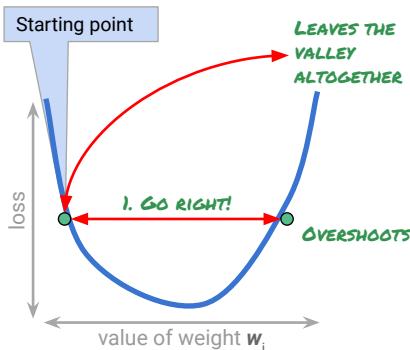
Typical batch size = 100-500 samples.

Learning rate is an important hyperparameter

Small step sizes can take a very long time to converge

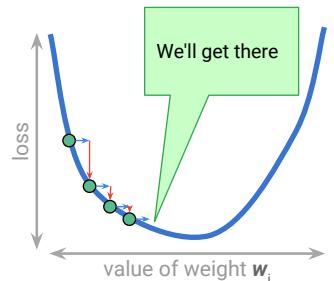


Large step sizes may never converge to the true minimum



A correct and constant step size can be difficult to find

STEP SIZE OR "LEARNING RATE" IS A HYPER-PARAMETER WHICH IS SET BEFORE TRAINING



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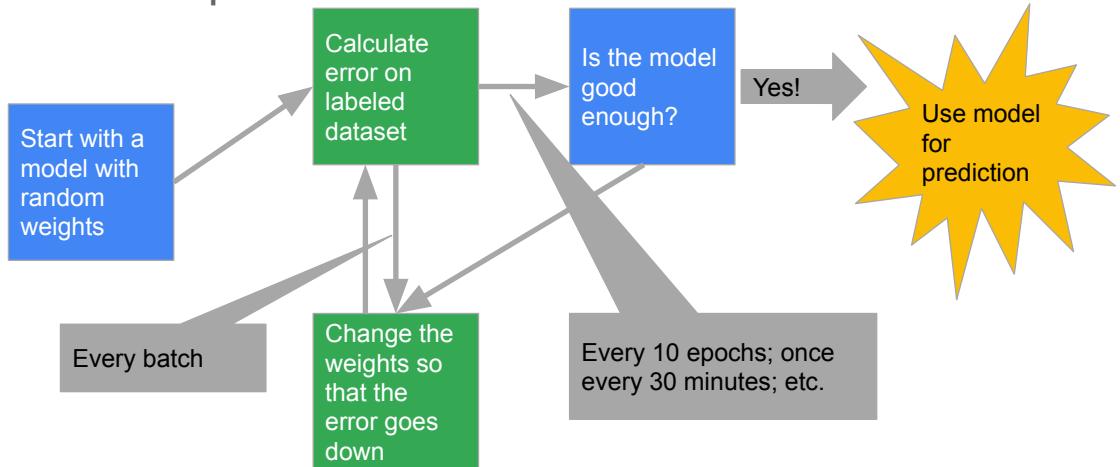
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Small step sizes: Putting aside direction for the moment, if your step size is too small, your training might take forever. You are guaranteed to find the minimum though (so long as there is only one minimum like this linear regression loss curve here -- remember our two minimum loss surface we just showed previously? We'll cover how to deal with those efficiently later).

Larger step sizes: If your step size is too big, you might either bounce from wall to wall or bounce out of your valley entirely, and into an entirely new part of the losos surface. Because of this, when the step size is too big, the process is not guaranteed to converge.

Correct step size: If your step size is just right Well, then, you're set. But whatever this value is, it's unlikely to be just as good on a different problem.

Occasionally, evaluate model to decide whether to stop



Notes:

Note that after we calculate error on batch, we can either keep going or we can evaluate the model.

Evaluating the model needs to happen on full dataset, not just a small batch!

Do Now: <http://goo.gl/5aZjBF>

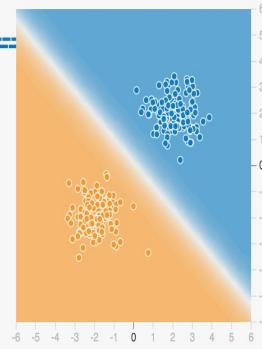
x_1

x_2

x_1^2

x_2^2

$x_1 x_2$



Notes:

Playground URL for this pattern: <http://goo.gl/5aZjBF>

Do Now: In your own words, write down definitions for these ML terms

Term	Meaning
Weights	
Batch size	
Epoch	
Gradient descent	
Evaluation	
Training	

Notes:

Weights/bias = parameters we optimize

Batch size = the amount of data we compute error on

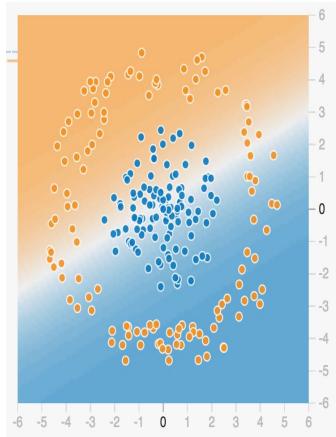
Epoch = one pass through entire dataset

Gradient descent = process of reducing error

Evaluation = is the model good enough? Has to be done on full dataset

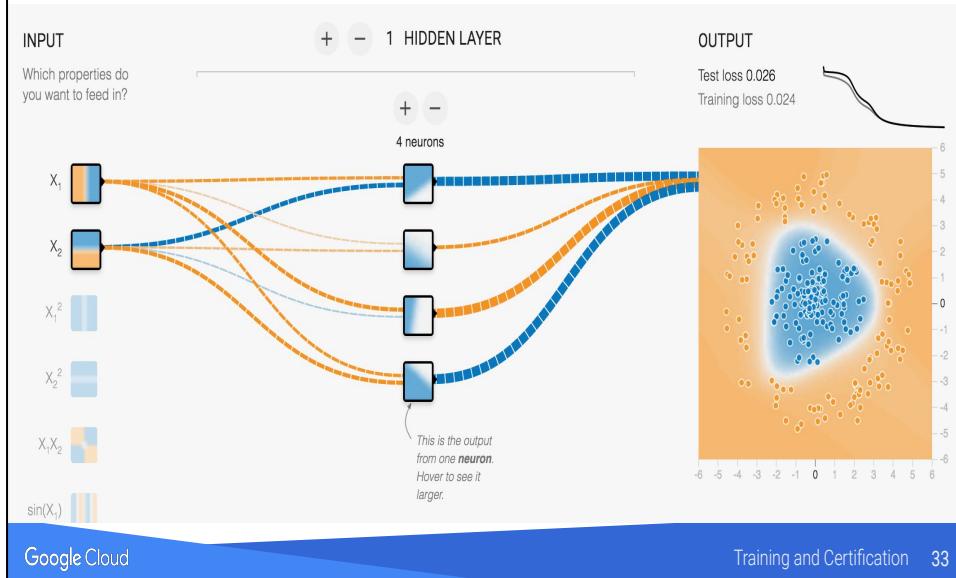
Training = process of optimizing the weights; includes gradient descent + evaluation

Do Now: Can you use a single line to separate these? What do you have to do?



<http://goo.gl/v7qM4Q>

More neurons \Rightarrow more input combinations (features)

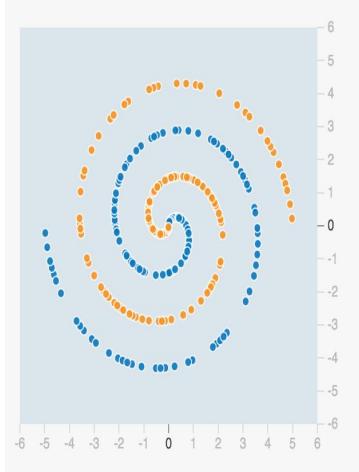


Notes:

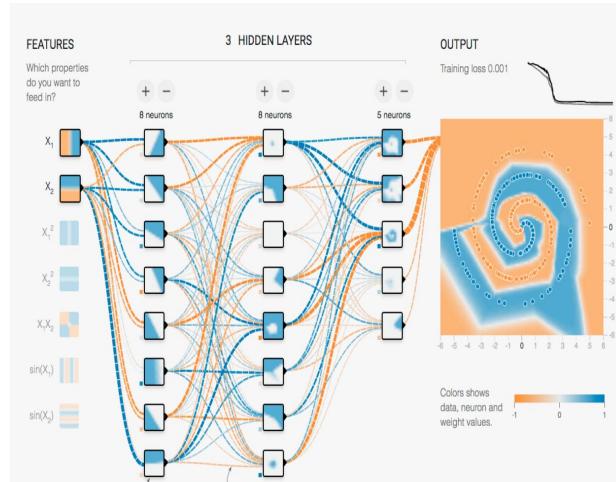
Note that the separation boundary is a polygon ... each side is a linear combination of features We should have gotten a 4-sided polygon, but in the diagram above two of the sides merged (i.e., their weights were linearly correlated).

Playground URL for this pattern: <http://goo.gl/rSX7Ve>

How about this? Will a set of lines work?



More hidden layers \Rightarrow more hierarchies of features



<http://goo.gl/fymPMI>

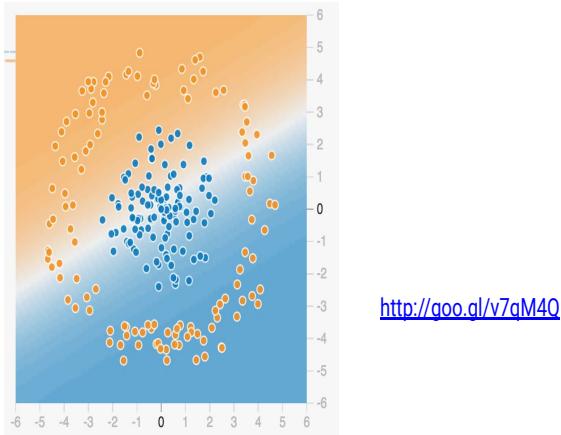
Google Cloud

Training and Certification 35

Notes:

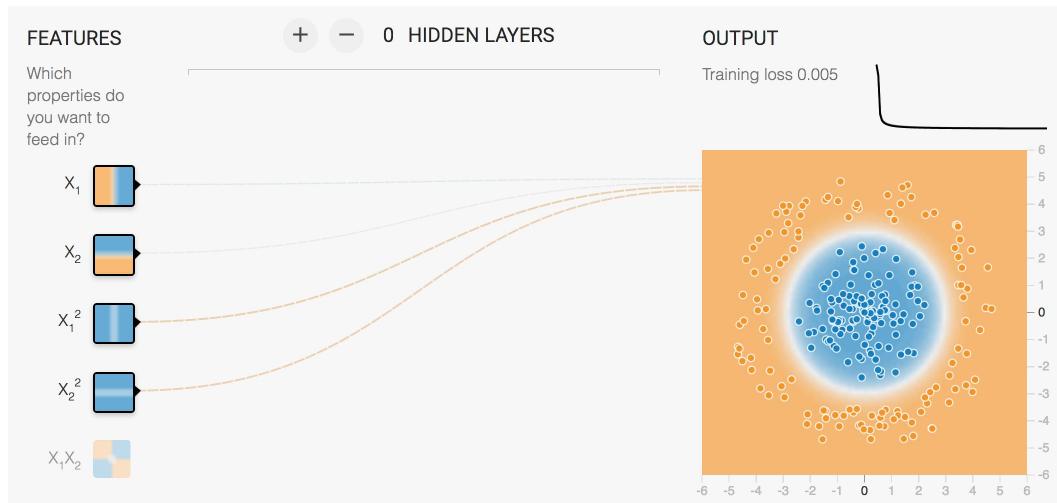
Even a complex non-linear pattern such as the double spiral could be classified by the simple neural network.

Do Now: Can you use a single line to separate these without adding layers?



<http://goo.gl/v7qM4Q>

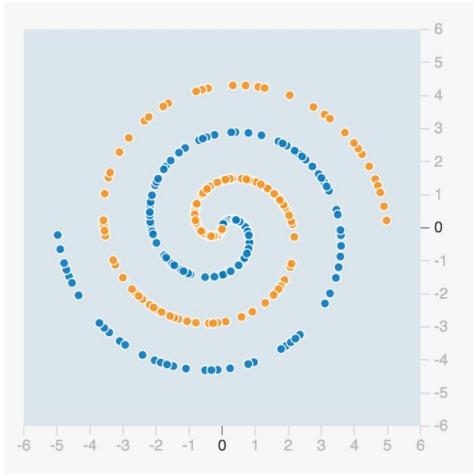
Engineer some extra features



Notes:

The reason we know that x^2 and y^2 will work is because we realize that points close to the origin are blue and those far away are orange. This indicates that distance would be a good feature, hence $x^2 + y^2 \dots$

These features help in the spiral case too...



<http://goo.gl/jdvKga>

Do Now: In your own words, write down definitions for these ML terms

Term	Meaning
Neurons	
Hidden layer	
Inputs	
Features	
Feature Engineering	

Notes:

Neuron = one unit of combining inputs

Hidden layer = set of neurons that operate on the same set of inputs

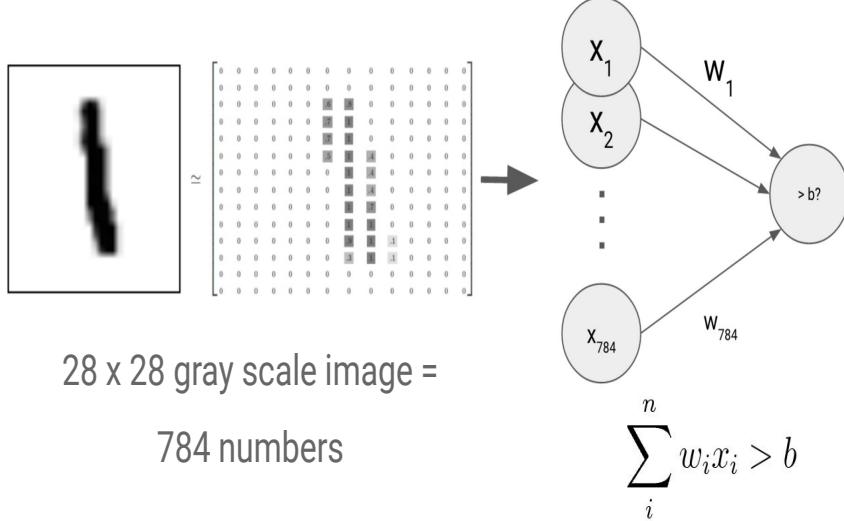
Features = transformations of inputs, such as x^2

Feature engineering = coming up with what transformations to include

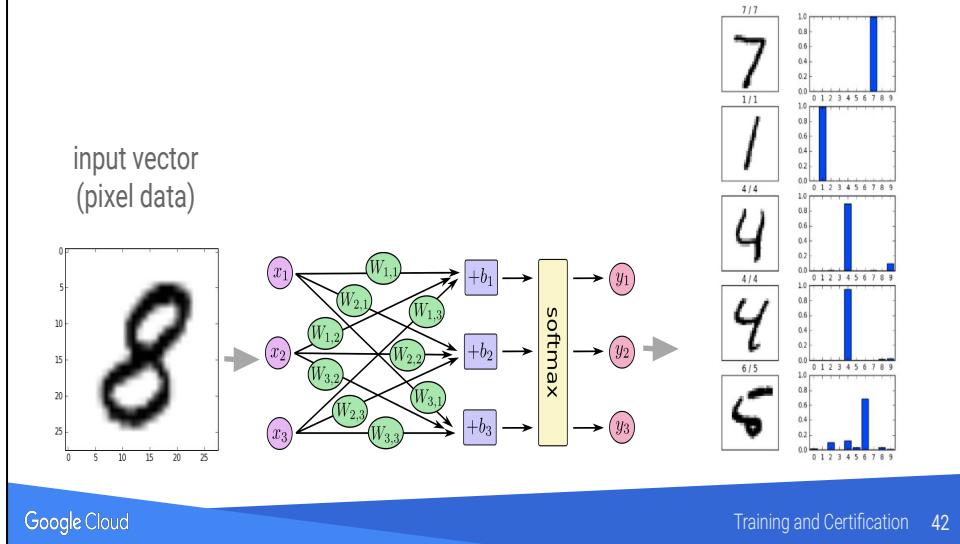
What about images? How does it work?



Each pixel value is an input



The softmax helps deal with multiple labels



Agenda

Effective ML

Google Cloud

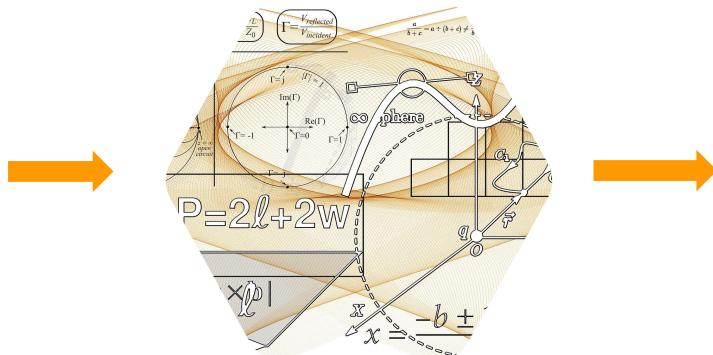
Training and Certification 43

20-40 minutes based on audience.

The popular imagination of what ML is



Lots of data



Complex mathematics in multidimensional spaces



Magical results

Google Cloud

Training and Certification 44

Notes:

<https://pixabay.com/en/x-y-mathematics-equation-937883/> (cc0)

<https://pixabay.com/en/mathematics-formula-physics-school-1233876/> (cc0)

<https://pixabay.com/en/deer-statue-silhouette-animal-stag-732122/> (cc0)

In reality, ML is...



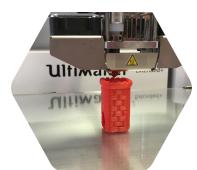
Collect data



Organize data



Create model



Use machines to
flesh out the
model from data



Deploy fleshed
out model

Notes:

<https://pixabay.com/en/ant-brown-carrying-egg-white-44588/> (cc0)

<https://pixabay.com/en/tile-organization-exterior-materials-846016/> (cc0)

<https://pixabay.com/en/deer-dream-animal-fantasy-1333814/> (cc0), cropped

<https://pixabay.com/en/printer-3d-pressure-3d-printing-1455169/> (cc0)

<https://pixabay.com/en/deer-statue-silhouette-animal-stag-732122/> (cc0)

On GCP, we can use:

Logging APIs, Cloud Pub/Sub, etc. and other real-time streaming to collect the data.

BigQuery, Dataflow and ML preprocessing SDK to organize the data [different types of organization].

TensorFlow to create the model.

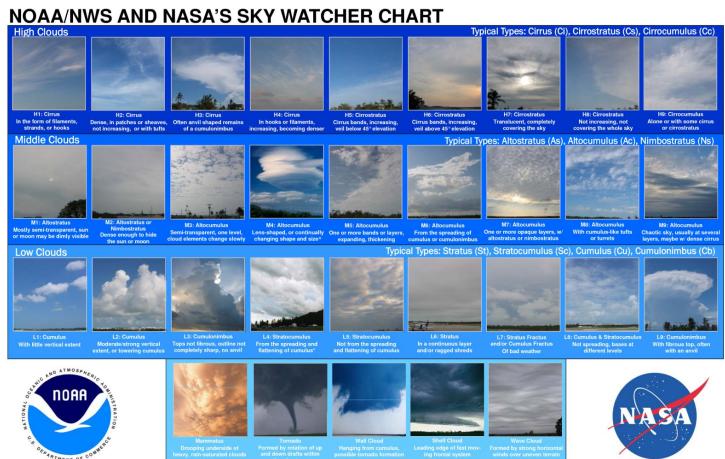
Cloud ML to train, deploy the model.

The magic is still there ...

The Dataset should cover all cases



All types covered?



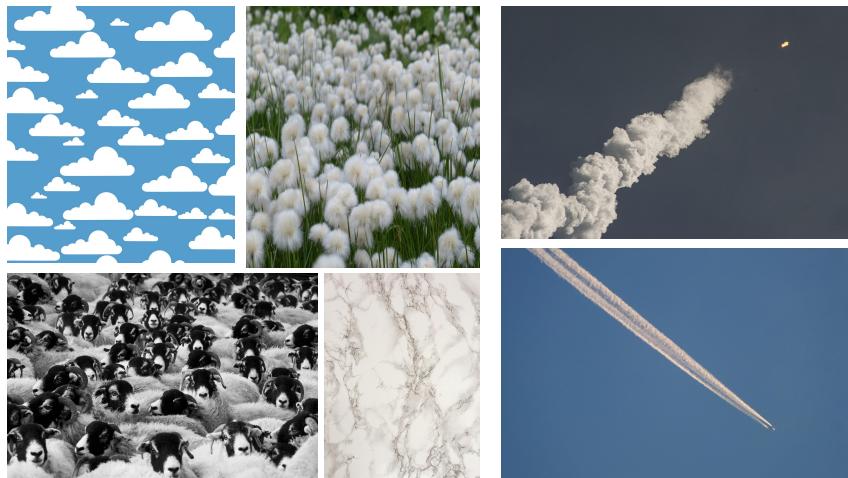
Notes:

If you are going to recognize clouds, make sure you know what all types of clouds there are, and collect enough images of each type. Domain experts have to be involved in creating the dataset for ML. But this isn't enough ... (see next slide)

Image source:

The left-hand side is a snapshot of several cc0 images from Pixabay.
Right-hand side is from NOAA/NWS and NASA. so public domain.

Negative examples and near-misses



Notes:

<https://pixabay.com/en/clouds-sky-blue-cumulus-white-34027/> (cc0) cartoon cloud

<https://pixabay.com/en/sheep-agriculture-animals-17482/> (cc0) flock of sheep

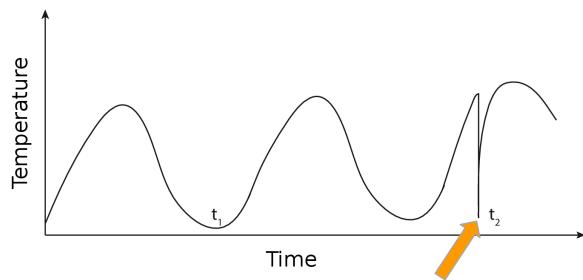
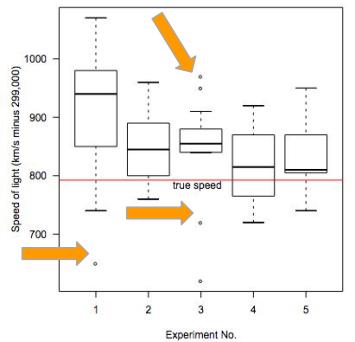
<https://pixabay.com/en/scheuchzers-cottongrass-175409/> (cc0) field of cotton

<https://pixabay.com/en/marble-background-backdrop-1006628/> (cc0) floor tile texture is cloud-like

<https://pixabay.com/en/rocket-launch-steam-smoke-trail-693270/> (cc0) is a steam from a rocket

<https://pixabay.com/en/chemtrail-conspiracy-theory-contrail-822000/> (cc0) is a chemtrail from plane

Explore the data you have; fix problems

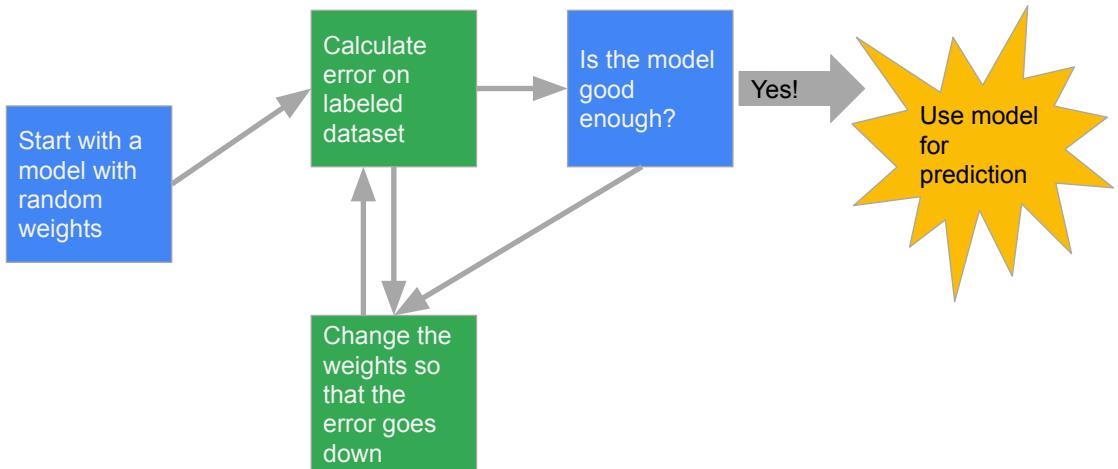


Notes:

Figure out what happened at the marked data points. It might be instrument errors, or worse.

Images from wikipedia page on outliers.

How do we compute error metrics?



Start from the outcome for a single example

ML system says you'll **win \$89**.

Truth: You **lose \$14**.



Notes:

Image: <https://pixabay.com/en/gallop-horse-horse-racing-1117183/>

Regression error: How far from true outcome?

ML system says you'll **win \$89**.

Truth: You **lose \$14**.

Your outcome is the error.

$$\begin{aligned}\text{Error} &= \text{truth} - \text{prediction} \\ &= \textcolor{red}{-\$14} - \textcolor{green}{\$89} = -\$103\end{aligned}$$



Notes:

Image: <https://pixabay.com/en/gallop-horse-horse-racing-1117183/>

Calculating regression error—Outcomes

-\$103
+\$75
-\$10
+\$99
-\$113
+\$82
+\$56



Notes:

Top Right Image: <https://pixabay.com/en/gallop-horse-horse-racing-1117183/>
Bottom Right Image: <https://pixabay.com/en/race-horses-racecourse-744105/>

Calculating regression error

1) Get the **error**:

-\$103	10609
+\$75	5625
-\$10	100
+\$99	9801
-\$113	12769
+\$82	6724
+\$56	3136

2) **Square** the error:



3) Calculate the **mean**:

6966

MSE

mean squared error

Notes:

Image: <https://pixabay.com/en/gallop-horse-horse-racing-1117183/>

Mathematically...

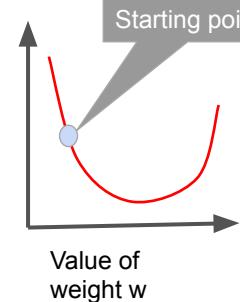
\hat{Y} -cap is the model estimate

Y is the labeled value

Mean Square Error (MSE) is:

$$\frac{1}{n} \sum_{i=1}^n (\hat{Y}_i - Y_i)^2$$

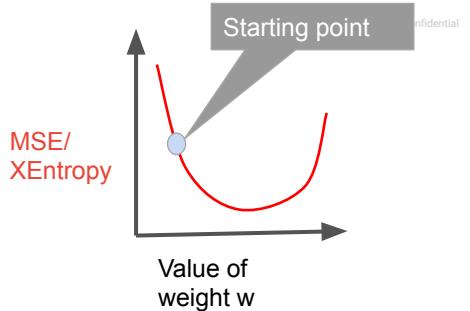
MSE



Notes:

Mathematically speaking, we prefer differentiable error measures so that we can do gradient descent. Mean-square error is differentiable.

For classification problems, we use cross-entropy



For classification problems, the most commonly used error measure is cross-entropy—because it is differentiable:

$$-\frac{1}{N} \sum_{n=1}^N \left[y_n \log \hat{y}_n + (1 - y_n) \log(1 - \hat{y}_n) \right]$$

Notes:

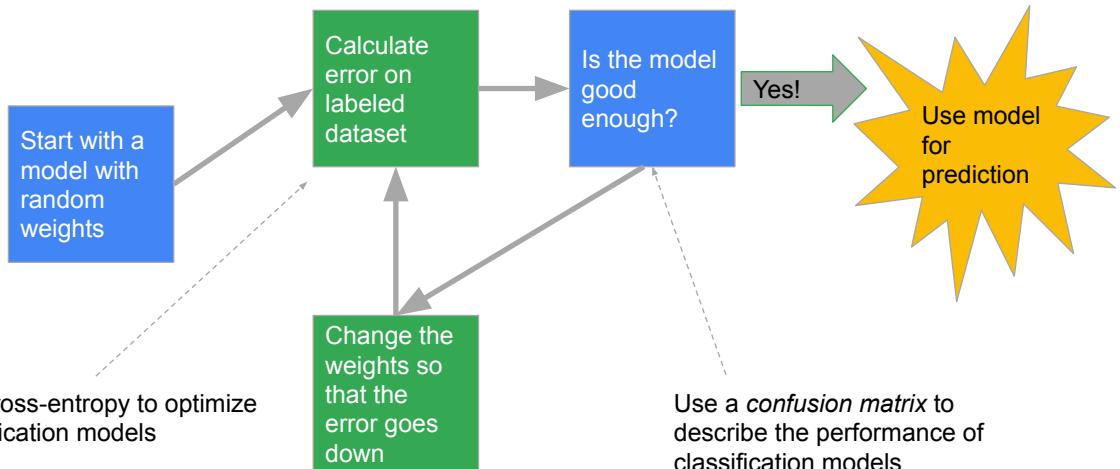
Mathematically speaking, we prefer differentiable error measures so that we can do gradient descent. So, for classification, we'll use cross-entropy.

Why cross-entropy for categorical variables? See:

https://en.wikipedia.org/wiki/Cross_entropy#Cross-entropy_error_function_and_logistic_regression.

In non-mathematical terms: You use a neural network whose output node is a soft-max (so that outputs are restricted to $[0,1]$) and whose objective function is cross-entropy. The result of the NN can be treated as a probability. So if you train using data on whether a customer bought your product or did not buy the product and you train on that data using the right NN structure, the trained NN can be used to estimate the probability that a visitor to your website will buy your product! This is hugely useful.

Cross-entropy is not intuitive to business users



Confusion matrix



1) Get the outcomes

TN

FP

TP

FN

TP

FN

		ML System Says	
		Cat	No Cat
Truth	Cat	True Positive #TP	False Negative #FN
	No Cat	False Positive #FP	True Negative #TN

Notes:

Get the outcome for each image in dataset, then add them up

Image: clipart <https://pixabay.com/en/cartoon-cat-cute-1292872/>

Confusion matrix is great, but it is 4 numbers and business decision makers want to see only one. Which one?

Accuracy, precision, and recall

Classify the cats!



Notes:

Image: cat with shoes courtesy of course author, Cassie Kozyrkov

Images: <https://pixabay.com/en/cat-cat-face-sleep-exhausted-1551810/>

<https://pixabay.com/en/cat-pet-mirror-697113/>

<https://pixabay.com/en/tiger-sumatran-sumatran-tiger-164905/>

<https://pixabay.com/en/cat-wink-funny-fur-animal-red-1333926/>

<https://pixabay.com/en/huskies-dog-animal-blue-eyes-view-1370230/>

<https://pixabay.com/en/goldhamster-hamster-animal-nuts-943373/>

<https://pixabay.com/en/racoon-animal-garden-summer-1453600/>

Hypothetical results from ML



Notes:

Image: cat with shoes courtesy of course author, Cassie Kozyrkov

Images: <https://pixabay.com/en/cat-cat-face-sleep-exhausted-1551810/>

<https://pixabay.com/en/cat-pet-mirror-697113/>

<https://pixabay.com/en/tiger-sumatran-sumatran-tiger-164905/>

<https://pixabay.com/en/cat-wink-funny-fur-animal-red-1333926/>

<https://pixabay.com/en/huskies-dog-animal-blue-eyes-view-1370230/>

<https://pixabay.com/en/goldhamster-hamster-animal-nuts-943373/>

<https://pixabay.com/en/racoon-animal-garden-summer-1453600/>

<https://pixabay.com/en/cartoon-cat-cute-1292872/>

Accuracy is fraction correct

$$\text{Accuracy} = 3 / 8 \\ = 0.375$$



Notes:

Image: cat with shoes courtesy of course author, Cassie Kozyrkov

Images: <https://pixabay.com/en/cat-cat-face-sleep-exhausted-1551810/>

<https://pixabay.com/en/cat-pet-mirror-697113/>

<https://pixabay.com/en/tiger-sumatran-sumatran-tiger-164905/>

<https://pixabay.com/en/cat-wink-funny-fur-animal-red-1333926/>

<https://pixabay.com/en/huskies-dog-animal-blue-eyes-view-1370230/>

<https://pixabay.com/en/goldhamster-hamster-animal-nuts-943373/>

<https://pixabay.com/en/racoon-animal-garden-summer-1453600/>

<https://pixabay.com/en/cartoon-cat-cute-1292872/>

<https://pixabay.com/en/check-mark-tick-mark-check-correct-1292787/>

<https://pixabay.com/en/incorrect-delete-remove-cancel-red-294245/>

Accuracy fails if dataset unbalanced



1000 parking spaces
990 of them are **taken**
10 are **available**

A ML model that
identified only **one** of the
ten **available** spaces:

Accuracy = $991/1000$
= 0.991!

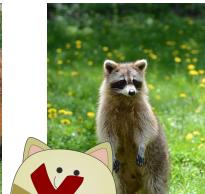
Notes:

Accuracy is fine for well-balanced datasets, but the dataset has a lot more of one category than another, we need to dig a little deeper into the performance. Use precision and recall for that. Suppose you have 1000 people and only 10 thieves. The ML can achieve 99.9% accuracy by classifying everything as "nice-people". This is where it is helpful to know that recall=0.

<https://pixabay.com/en/parking-autos-vehicles-traffic-825371/> (cc0)

Precision = Positive Predictive Value

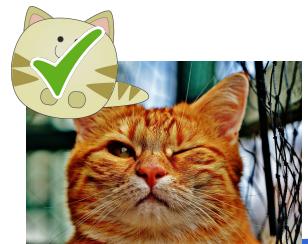
Accuracy when
ML says “cat”



$$TP + FP = 5$$



$$\begin{aligned} \text{Precision} &= TP / (TP + FP) \\ &= 2 / 5 = 0.40 \end{aligned}$$



Notes:

Ask them what the precision is for the parking-lot example.

Answer: Depends on what you define as “positive”.

We have to define “available” as positive since that’s what we want to predict ...

Answer: Precision = 1/1 = 1 because all our predictions of “available” are correct.

When we are sure, we are sure.

Image: cat with shoes courtesy Cassie Kozyrkov, Google

Images: <https://pixabay.com/en/cat-cat-face-sleep-exhausted-1551810/>

<https://pixabay.com/en/cat-pet-mirror-697113/>

<https://pixabay.com/en/tiger-sumatran-sumatran-tiger-164905/>

<https://pixabay.com/en/cat-wink-funny-fur-animal-red-1333926/>

<https://pixabay.com/en/huskies-dog-animal-blue-eyes-view-1370230/>

<https://pixabay.com/en/goldhamster-hamster-animal-nuts-943373/>

<https://pixabay.com/en/racoon-animal-garden-summer-1453600/>

<https://pixabay.com/en/cartoon-cat-cute-1292872/>

<https://pixabay.com/en/check-mark-tick-mark-check-correct-1292787/>

<https://pixabay.com/en/incorrect-delete-remove-cancel-red-294245/>

Recall is true positive rate

$$\text{Recall} = \frac{\text{fraction of cats ML finds}}{\text{TP} + \text{FN}} = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{2}{4} = 0.50$$



Notes:

Ask them what the recall is for the parking-lot example.

Answer: Recall = 1/10 = 0.1

Image: cat with shoes courtesy Cassie Kozyrkov, Google

Images: <https://pixabay.com/en/cat-cat-face-sleep-exhausted-1551810/>

<https://pixabay.com/en/cat-pet-mirror-697113/>

<https://pixabay.com/en/tiger-sumatran-sumatran-tiger-164905/>

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<https://pixabay.com/en/goldhamster-hamster-animal-nuts-943373/>

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<https://pixabay.com/en/cartoon-cat-cute-1292872/>

<https://pixabay.com/en/check-mark-tick-mark-check-correct-1292787/>

<https://pixabay.com/en/incorrect-delete-remove-cancel-red-294245/>

Do Now: In your own words, write down definitions for these ML terms

Term	Meaning
MSE	
Cross-entropy	
Accuracy	
Precision	
Recall	

Notes:

Mean Square Error: the loss measure for regression problems

Cross-entropy: the loss measure for classification problems

Accuracy: A more intuitive measure of skill for classifiers

Precision: Accuracy when classifier says “yes” (useful for unbalanced classes where there are many more yes-es than no-es)

Recall: Accuracy when the truth is “yes” (useful for unbalanced classes where there are very few yes-es)

ROC curve: a way to pick the threshold (of the probability that is output by the classifier) at which a specific precision or recall is reached. The area under the curve (AUC) is a threshold-independent measure of skill.

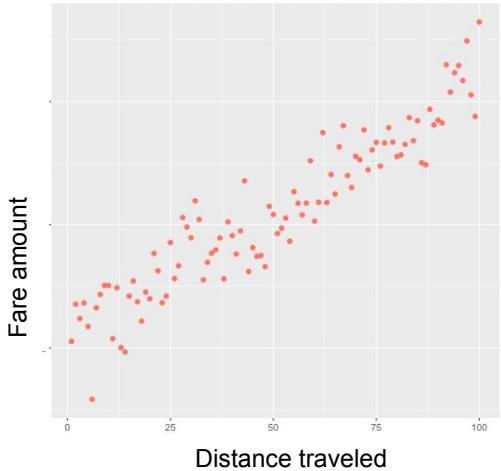
Agenda

Creating ML Datasets + Lab

Regression problem: Predict taxi fare

Problem: predict taxi fare amount based on distance traveled

What is the error measure to optimize?

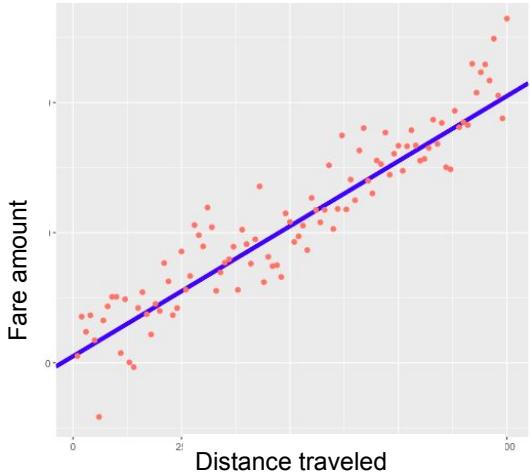


Model 1

Red = training data

Blue = model prediction for each distance traveled

RMSE = **22.24**



Notes:

Simulation by Cassie Kozyrkov, Google.

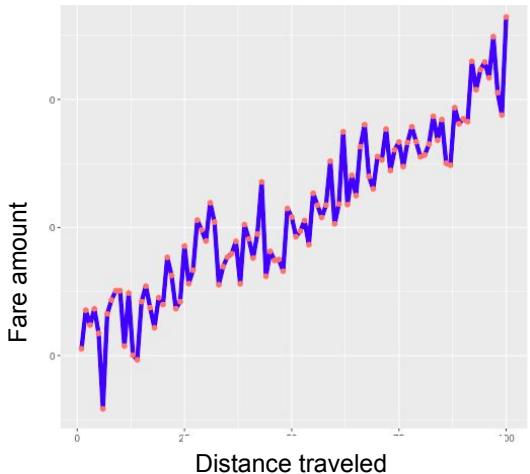
This is a linear model, so linear regression.

Model 2 has more free parameters

RMSE = 0

Which model is better?

How can we tell?



Notes:

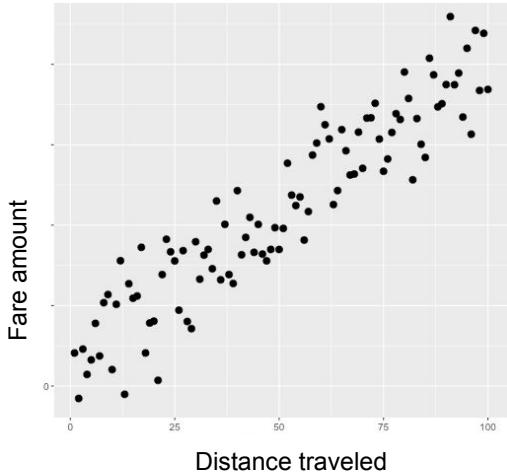
Simulation by Cassie Kozyrkov, Google.

This might be a polynomial of 100th order or a neural network with lots of nodes. A more complex model has more parameters that can be optimized. This can help it fit more complex data. But it might also help it memorize simpler datasets.

People intuitively feel that there is something fishy about Model 2. But how can we tell? In ML, we often have lots of data, and no such intuition. Is a NN with 8 nodes better than a NN with 12 nodes? The 12 nodes has lower RMSE ... so should we pick it? But what if we try 16 nodes, and it has even lower RMSE? At what point do we stop and say a model is now simply memorizing?

Does the model generalize to new data?

Need data that were not used
in training

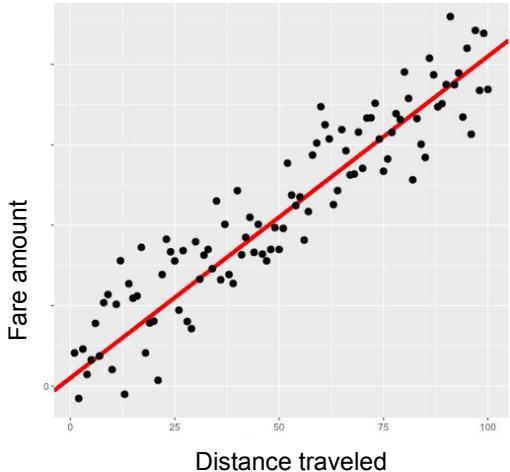


Model 1 generalizes well

Old RMSE = **22.24**

New RMSE = **21.98**

Pretty similar = good



Notes:

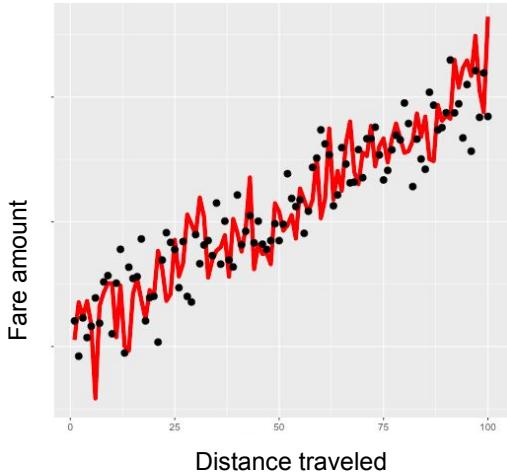
Simulation by Cassie Kozyrkov, Google.

Model 2 does not generalize well

Old RMSE = 0

New RMSE = 32

This is a red flag

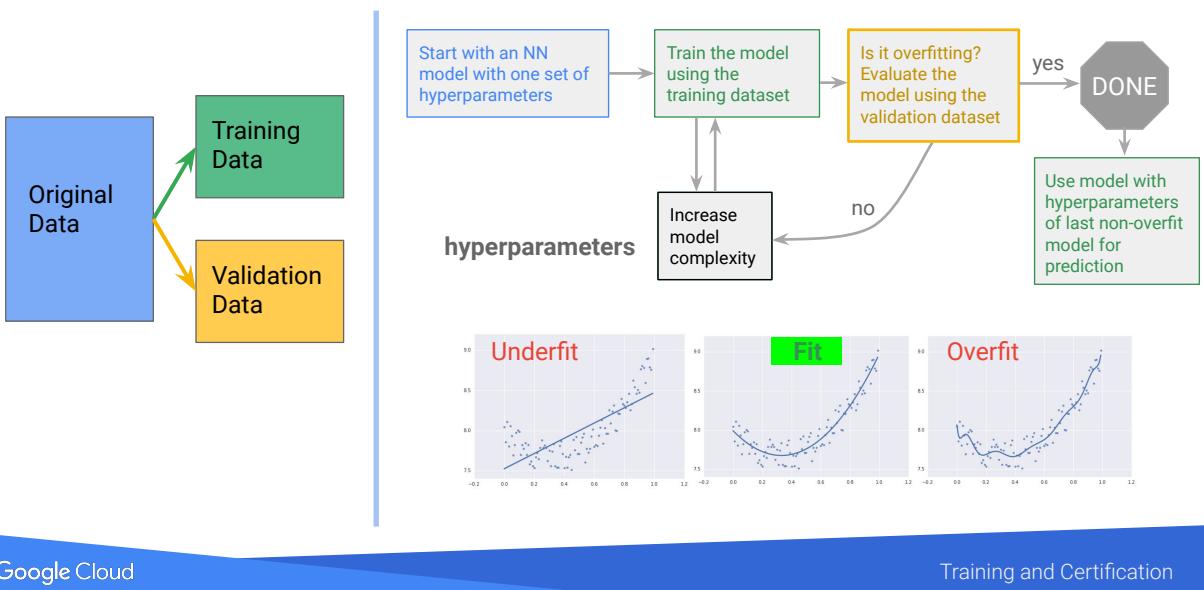


Notes:

Simulation by Cassie Kozyrkov, Google.

Split data, experiment with models

Proprietary + Confidential



Google Cloud

Training and Certification

Training and evaluating an ML model is an experiment with finding the right generalizable model that fits your training dataset but doesn't memorize it. As you see here, we have an overly simplistic linear model that doesn't fit the relationships in the data. You'll be able to see how bad this is immediately by looking at your loss metric during training (and visually on this graph here as there are quite a few points outside the shape of trend line). This is called underfitting.

On the opposite end of the spectrum is overfitting, as shown on the right extreme. Here we greatly increased the complexity of our linear model and turned it into an n-th order polynomial which seems to model the training dataset really well -- almost too well. This is where the evaluation dataset comes in -- you can use the evaluation dataset to determine if the model parameters are leading to overfitting. Overfitting or memorizing your training dataset can be far worse than having a model that only adequately fits your data.

Somewhere in between an underfit where the loss metric is not low enough and an overfit whether the model doesn't generalize is the right level of model complexity.

In addition to helping you choose between two completely different ML models (like regression or neural networks), you can also use your validation dataset to help fine-tune the hyperparameters of a single model which, if you recall, are set before training. This tuning process is accomplished through successive training runs and comparisons against your validation dataset to check for overfitting.

So here's how your validation dataset will actually be used after your model training. As you saw when we covered Optimization, training the model is where we start with random weights, calculate a loss metric on a batch of data, adjust the weights to minimize the loss metric, and repeat.

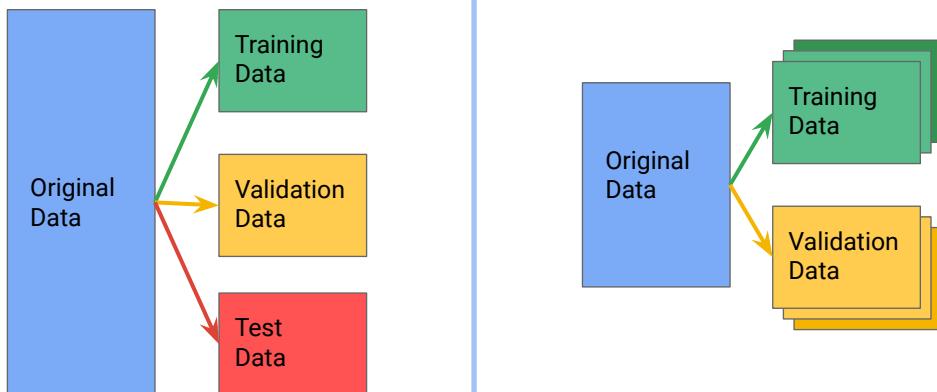
Periodically, we want to assess the performance of our model against data it has not yet seen in training which is where we use our validation dataset after a completed training run with the initial hyperparameters we set.

If there is not significant divergence between the loss metrics from the training run and the loss metric for the validation dataset then the model could still be optimized and tuned. We can go back to our hyperparameters that are set before training happens and try another training model run.

Perhaps we add one more layer to our neural network.

You can use a loop similar to this to also figure out model parameters like what we just did for hyperparameters, for example the number of layers or nodes to use in a neural network. Essentially, you will train with one configuration and evaluate on the validation dataset. Then, you will try out a different configuration that has more or fewer nodes and evaluate on the validation dataset. You will choose the model configuration that results in the lower loss on the validation dataset, not the model configuration that results in lower loss on the training one.

Use independent test data, or cross-validate if data is scarce



Google Cloud

Training and Certification

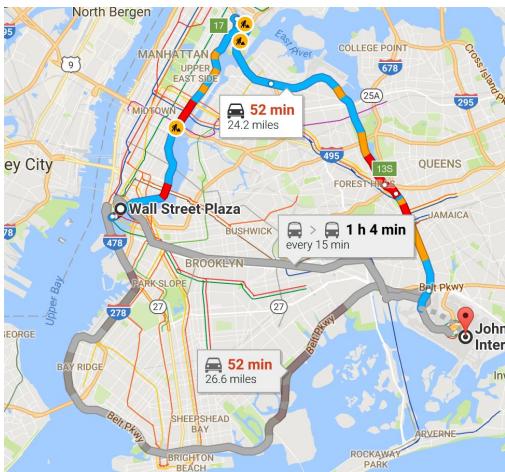
Notes

Cannot just use the original validation dataset. That is no longer truly independent.

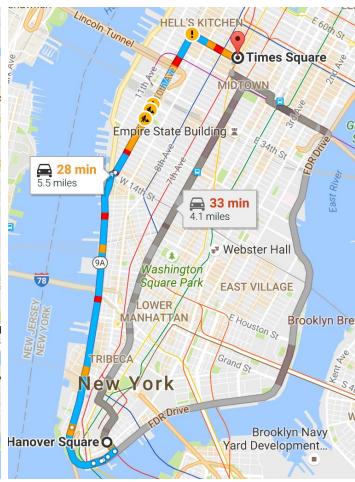
Cross-validation could be done in both cases on the ice cream cone example. If we do random sampling, it's just a matter of choosing a different seed. If we divide by days/month, it's just a matter of varying the cutoff day (it was the first 25 days in our example, but we could cycle through and take the middle 25 days). This also ensures that we don't throw away any data completely due to leakage.

Included in Option 2 is the idea of going ahead and using all of our data and allowing the passage of time to get us an independent test data.

Goal: To estimate taxi fare



http://www.nyc.gov/html/tlc/html/passenger/taxicab_rate.shtml



\$2.50 initial charge
+
50c per $\frac{1}{6}$ mile
(or)
50c per minute if stopped
+
Passenger pays tolls
+
Various special charges

Notes:

Left: a trip from Hanover Square to Time Square (downtown to midtown). Two routes – the shorter one takes longer.

Right: a trip from JFK to Manhattan offers 2 routes, both very roundabout as compared to what a bus would take. You pay a toll to take the triborough bridge

But assume we don't know any of these things. Instead of hardcoding a bunch of rules, let's try to infer the fare amount simply from the data. The point of ML is to program with data instead of rules.

<https://pixabay.com/en/question-mark-question-faq-ask-1421013/> (cc0)

Increasingly, data analysis and machine learning are carried out in self-descriptive, shareable, executable notebooks

Proprietary + Confidential

The screenshot shows a Google Cloud Datalab notebook titled "demandforecast (autosaved)". On the left, there's a vertical sidebar with four colored sections: "Share" (green), "Code" (blue), "Output" (yellow), and "Markup" (red). The "Code" section contains a snippet of Python code:

```
j = data[data['dayofweek'] == 7].plot(kind='scatter', x='maxtemp', y='numtrips')
```

. The "Output" section displays a scatter plot with "numtrips" on the y-axis (ranging from 50,000 to 85,000) and "maxtemp" on the x-axis (ranging from 20 to 100). The plot shows a general upward trend. Below the plot, a red-bordered text box contains a note:

Removing the confounding factor does seem to reflect an underlying trend around temperature. But ... the data are a little sparse, don't you think? This is something that you have to keep in mind -- the more predictors you start to consider (here we are using two: day of week and maximum temperature), the more rows you will need so as to avoid overfitting the model.



A TYPICAL
NOTEBOOK
CONTAINS CODE,
CHARTS, AND
EXPLANATIONS

Image Source:
[Git Logo from Wikipedia](#)

Google Cloud

Training and Certification

Do you use IPython or Jupyter notebooks today? Increasingly, data scientists work in self-descriptive, shareable, executable notebooks whenever they want to do data analysis or machine learning.

Datalab is based on Jupyter and it's open source.

Combines code, documentation, results, and visualizations together in an intuitive notebook format

Cloud Datalab is built on Jupyter (formerly IPython)

Python, SQL, and JavaScript

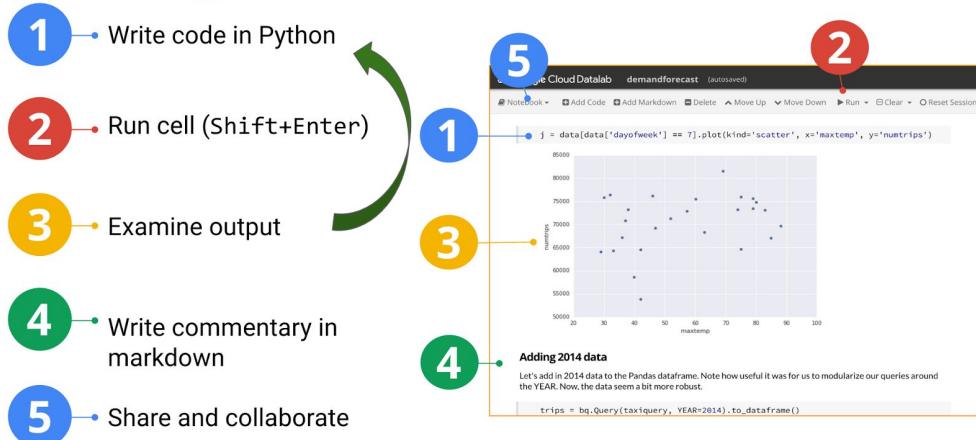
Supports Google Charting or matplotlib for easy visualizations

How to launch:

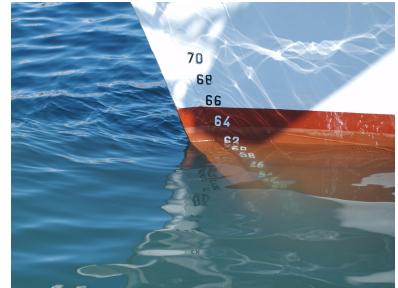
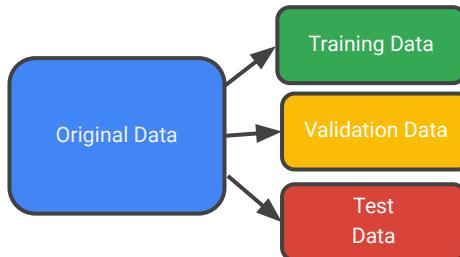
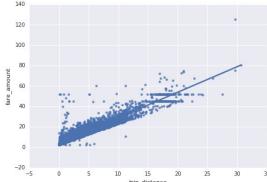
From Cloud Shell: `datalab create <vm-name>`

Or Cloud Dataproc Initialization action

How to work with Cloud Datalab



Lab 1: Explore dataset, create ML datasets, create benchmark



1. Explore

2. Create Datasets

3. Benchmark

Notes:

These should form the first steps for any ML project that you undertake. You will often spend weeks just exploring the dataset to gain intuition into the problem – this is crucial to creating good ML models. The benchmark phase should not be neglected; if you don't have a benchmark, you won't know what kind of performance you should seek to attain. Many times, errors can be detected simply by realizing that the performance of the ML model is nowhere near the benchmark.

<https://pixabay.com/en/ship-sea-water-blue-water-level-1518522/> (cc0)

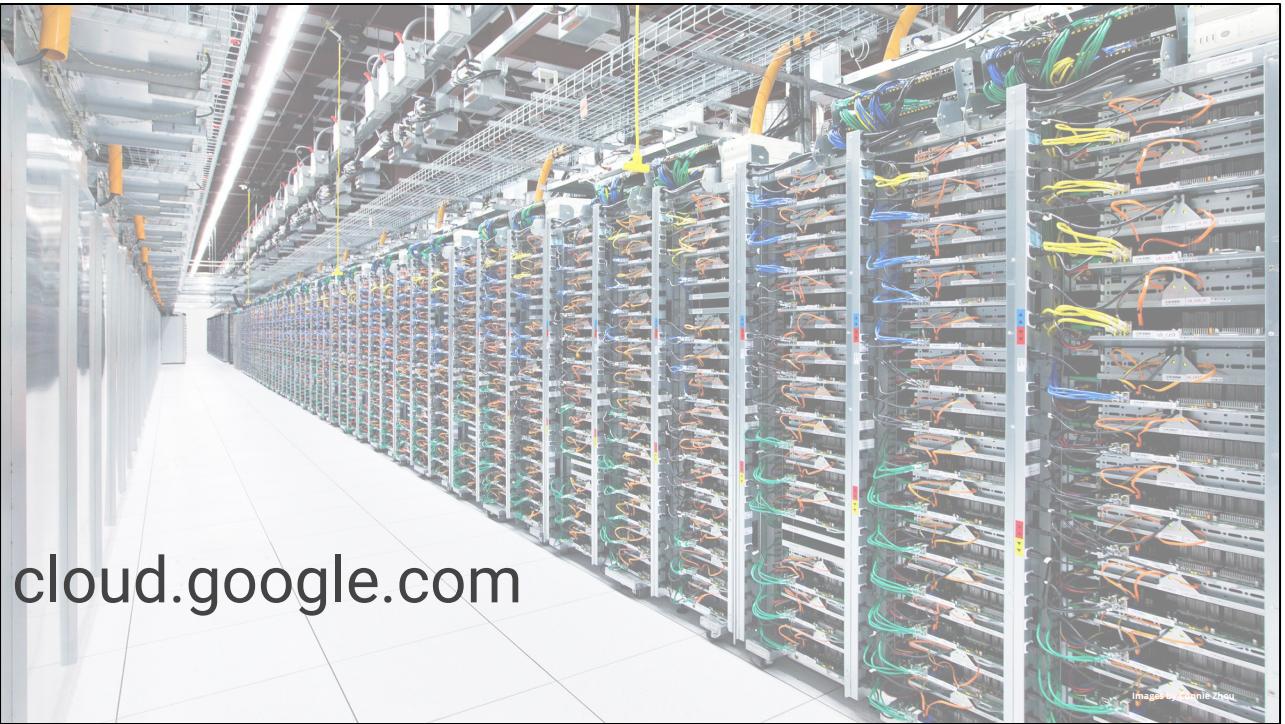


Image by Connie Zhou