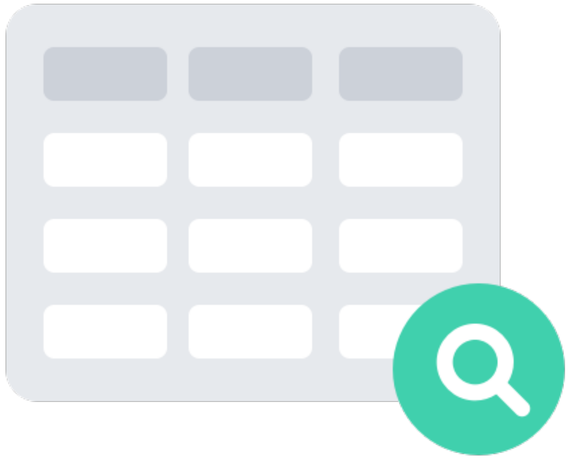
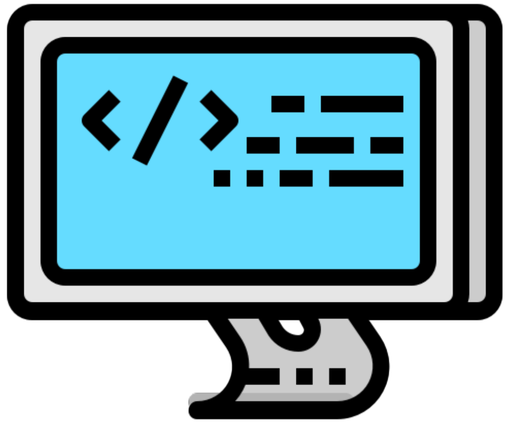
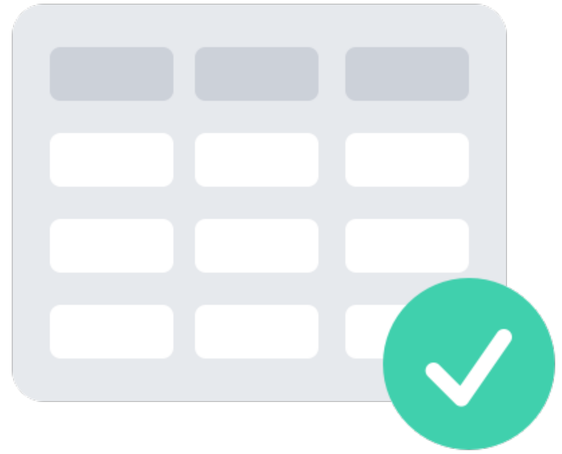
What is machine learning?



Data



Machine learning algorithm



Patterns

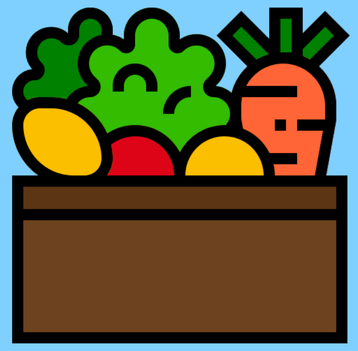
Future

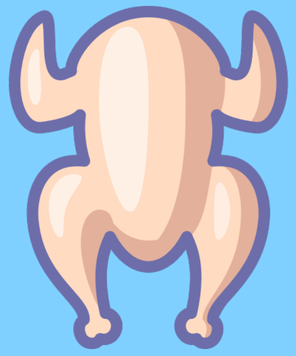
New data

Same algorithm (model)

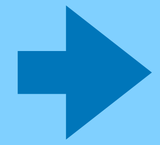
More patterns

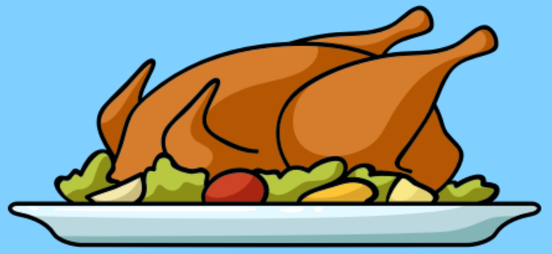
Normal algorithm





1. Cut vegetables
2. Season chicken
3. Preheat oven
4. Cook chicken for 30-minutes
5. Add vegetables



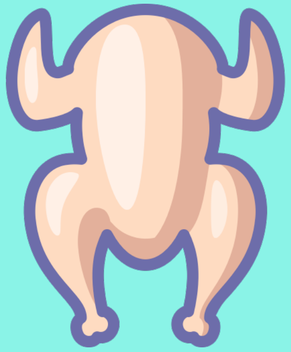


Starts with

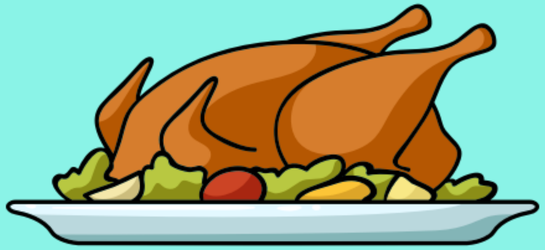
Makes

Machine learning algorithm

Inputs



Output



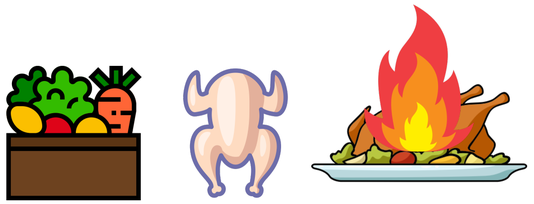
1. Cut vegetables
2. Season chicken
3. Preheat oven
4. Cook chicken for 30-minutes
5. Add vegetables

Starts with

Figures out

Attempt

1

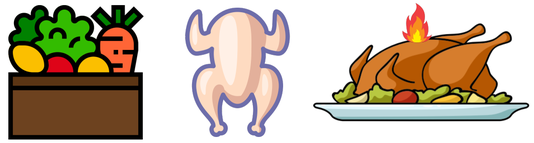


1. Cut vegetables
2. Season chicken with lots of spice
3. Preheat oven
4. Cook chicken for 30-minutes
5. Add vegetables

2

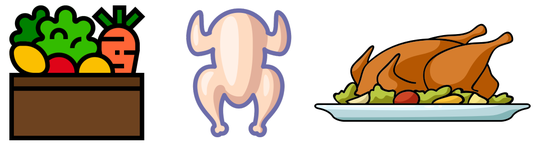
1. Cut vegetables
2. Season chicken with extra spice
3. Preheat oven
4. Cook chicken for 30-minutes
5. Add vegetables

3



1. Cut vegetables
2. Season chicken a lil' extra spice
3. Preheat oven
4. Cook chicken for 30-minutes
5. Add vegetables

4



1. Cut vegetables
2. Season chicken
3. Preheat oven
4. Cook chicken for 30-minutes
5. Add vegetables

⋮

1. Cut vegetables
2. Season chicken
3. Preheat oven
4. Cook chicken for 30-minutes
5. Add vegetables

100

1. Cut vegetables
2. Season chicken
3. Preheat oven
4. Cook chicken for 30-minutes
5. Add vegetables

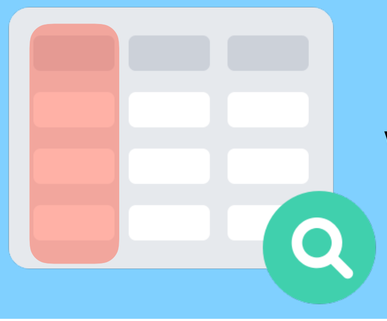
Machine learning algorithms may try 1000's of times to find the right instructions.

Data science

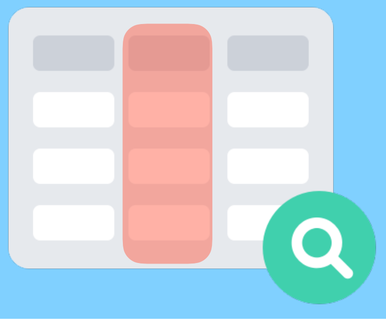
Data analysis

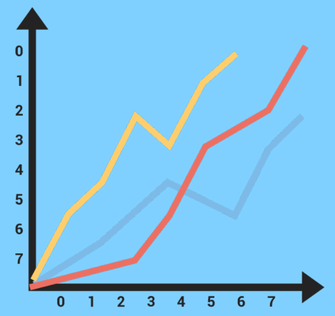
Data

vs.

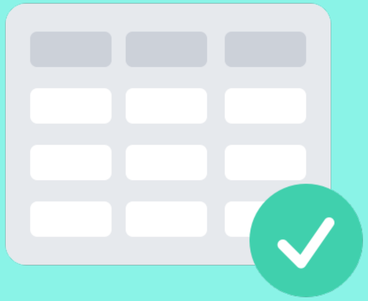


vs.





Machine learning



1. Cut vegetables
2. Season chicken
3. Preheat oven
4. Cook chicken for 30-minutes
5. Add vegetables

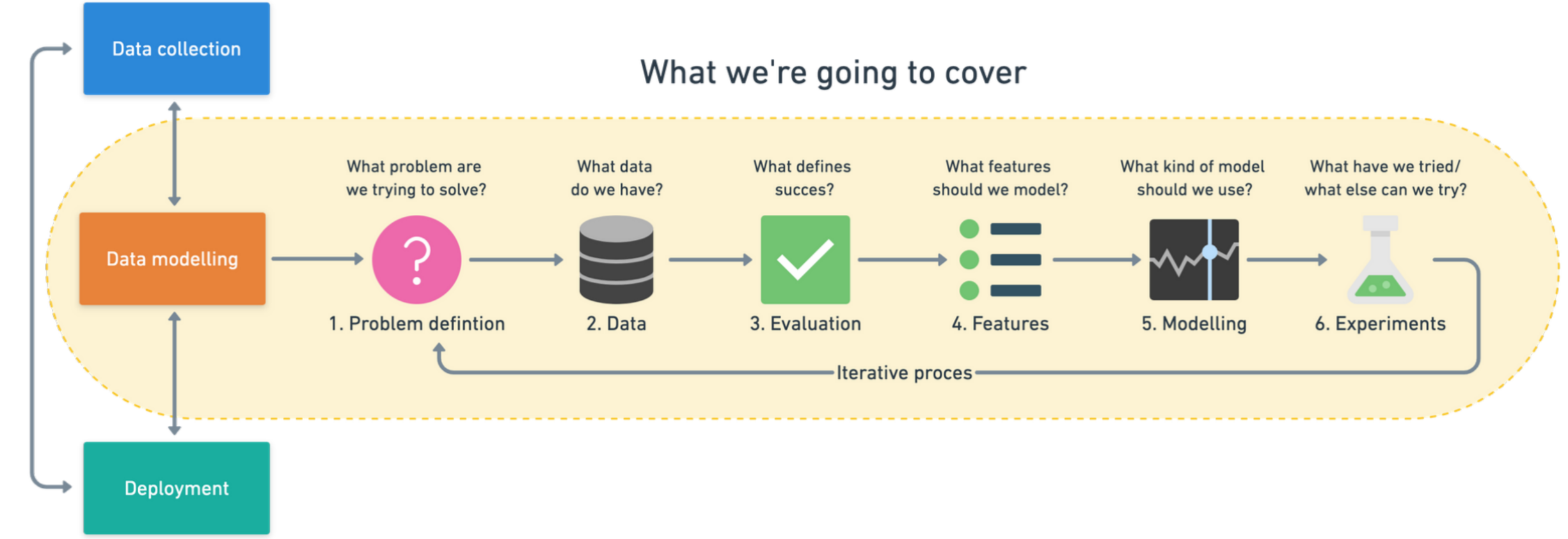
Instructions in your daily life?

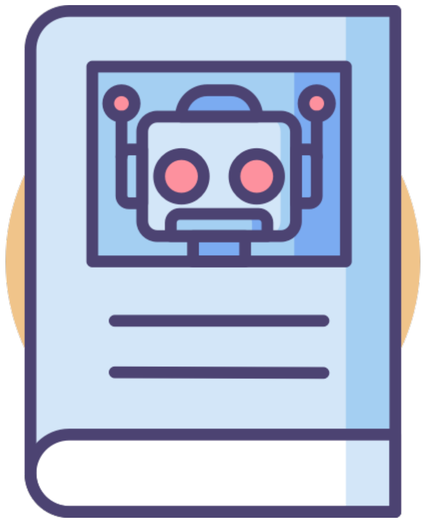
What we're going to cover (and what you'll finish with)

We're focused on...

- Practical solutions
- Writing machine learning code

Steps in a full machine learning project





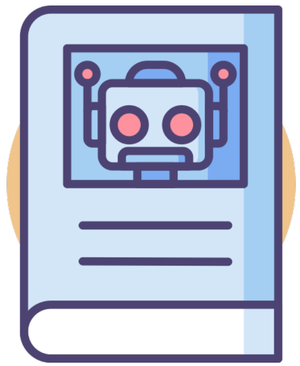
1. Create a framework

2. Match to data science and machine learning tools

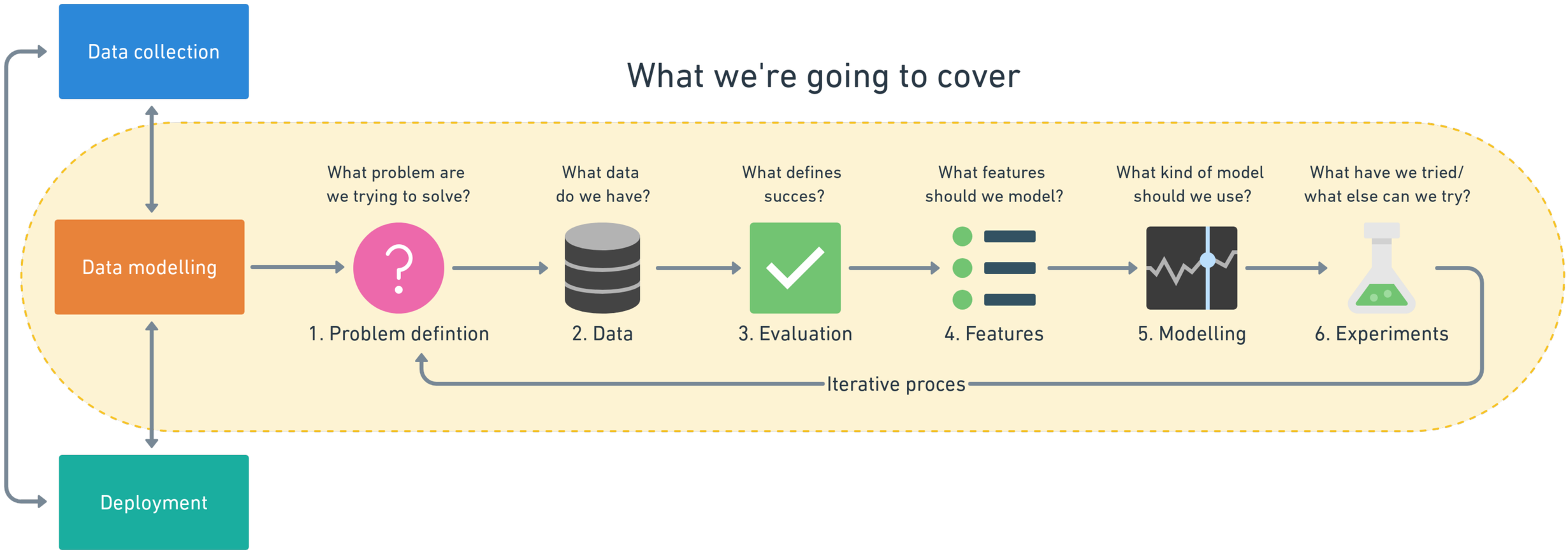
3. Learn by doing

Yes	No
Write code	Overthink the process
Make mistakes	Try make things perfect
Build projects	Build things from scratch
Learn what matters	

The framework we'll be using

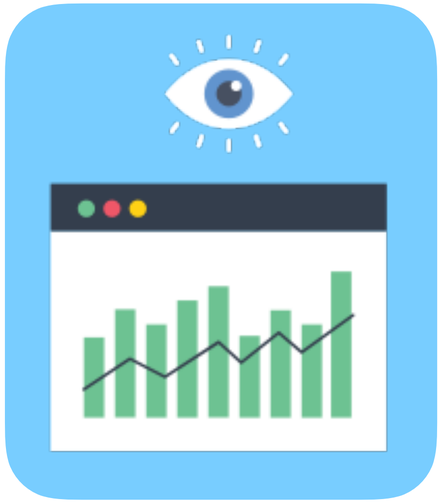


Steps in a full machine learning project



1. Problem definition

“What problem are we trying to solve?”



Supervised

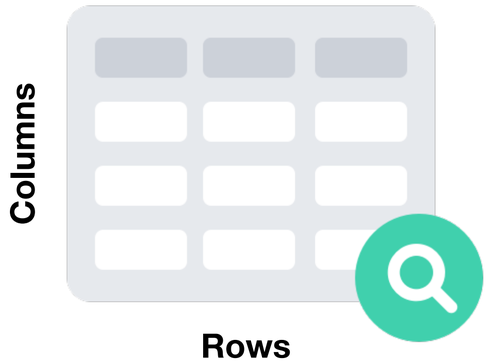
Unsupervised

Classification

Regression

2. Data

“What kind of data do we have?”



Structured

Unstructured

3. Evaluation

“What defines success for us?”

House data

Machine learning model

House price

Predicted price

$497,890

Actual price

$500,000

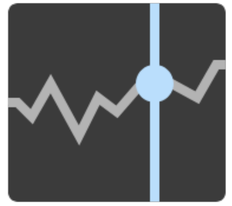
4. Features

“What do we already know about the data?”

ID	Weight	Sex	Blood Pressure	Chest pain	Heart disease?
4326	110kg	M	120/80	4	yes
5681	64kg	F	130/90	1	NO
7911	81kg	M	130/80	0	NO

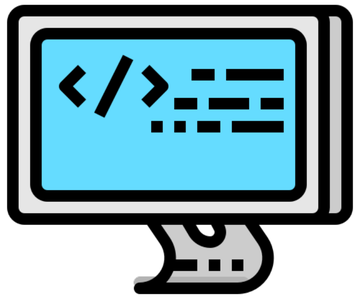
Table 1.0: Patient records

5. Modelling



“Based on our problem and data, what model should we use?”

Problem 1



Model 1

Problem 2

Model 2

6. Experimentation

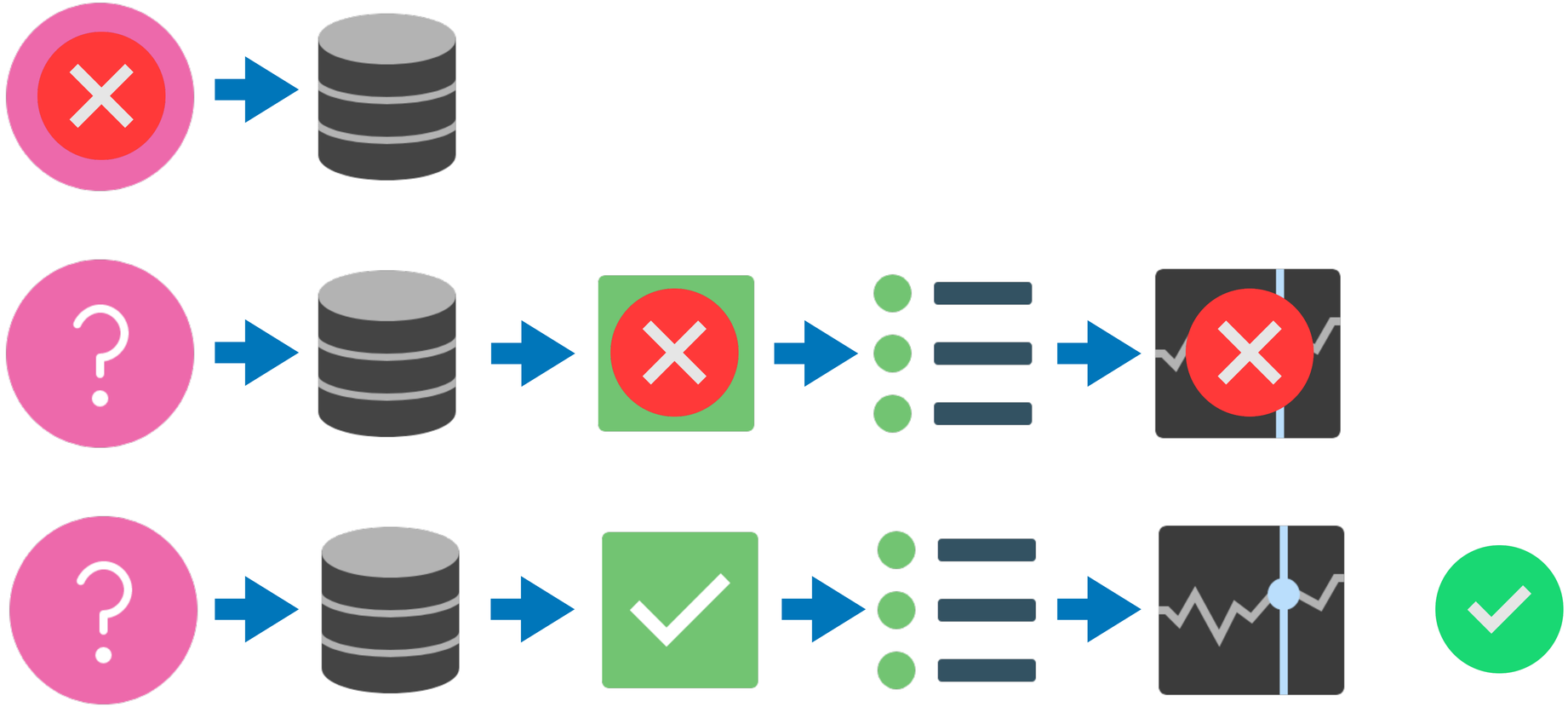
“How could we improve/what can we try next?”

Attempt

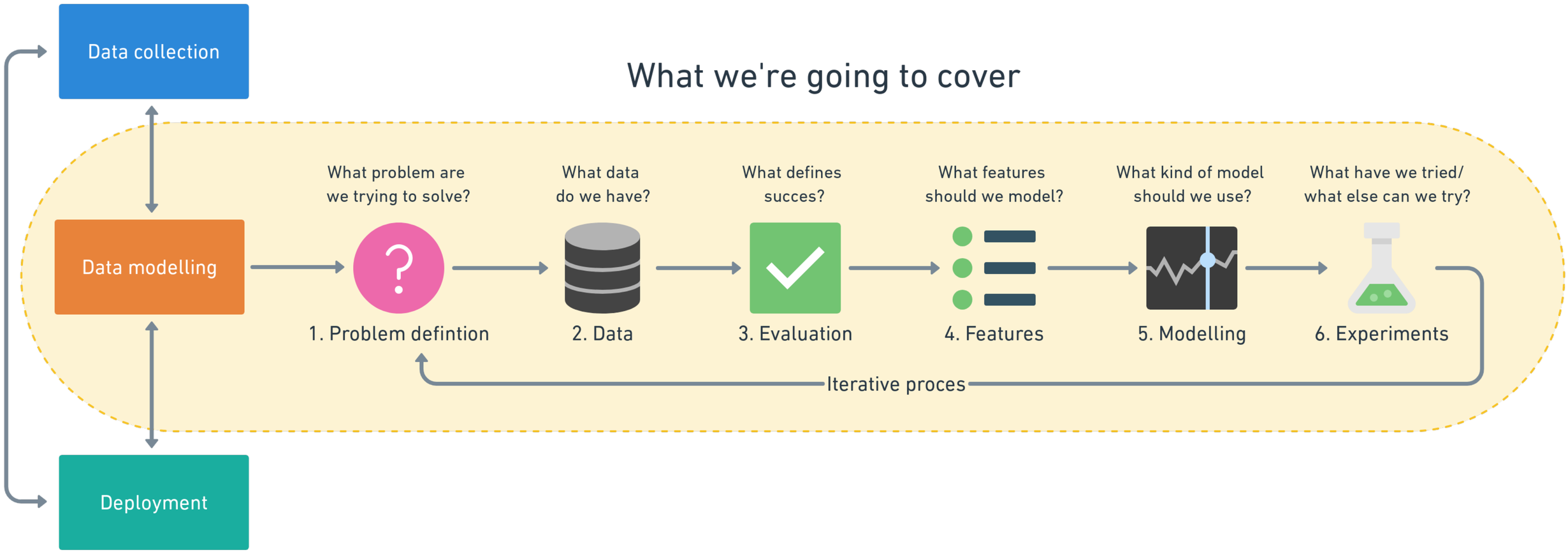
1

2

3



Steps in a full machine learning project

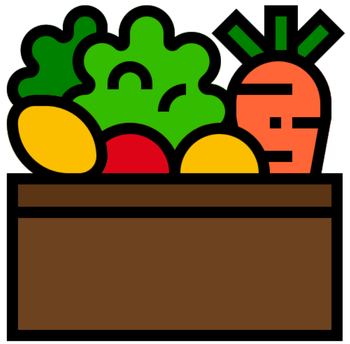


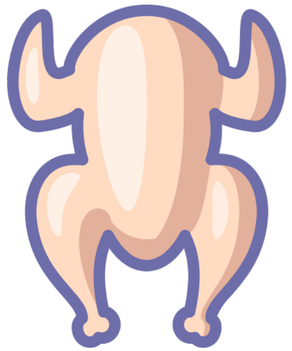
1. Problem definition

“What problem are we trying to solve?”

When shouldn’t you use machine learning?

- **Will a simple hand-coded instruction based system work?**





1. Cut vegetables
2. Season chicken
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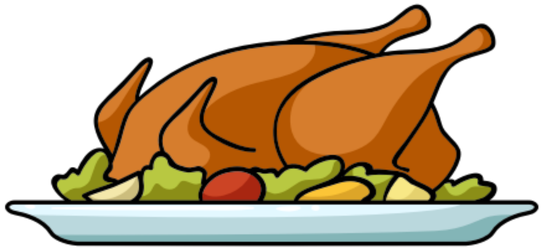
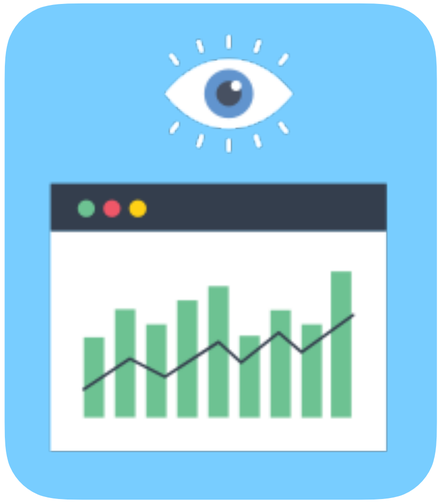
4. Cook chicken for 30-minutes
5. Add vegetables

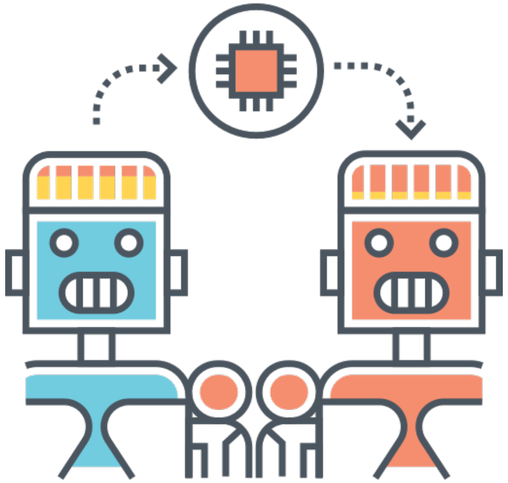


Main types of machine learning

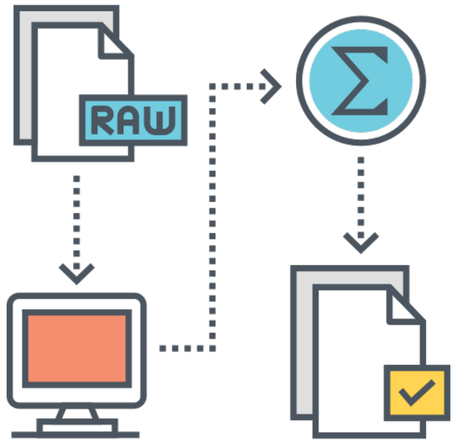


Supervised Learning

Unsupervised Learning

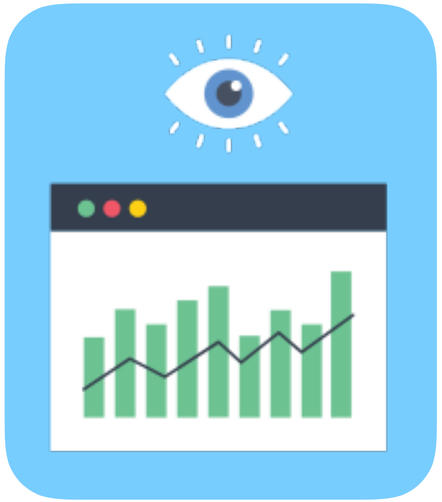


Transfer Learning

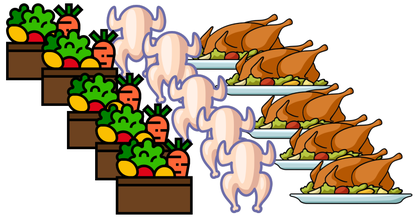


Reinforcement Learning

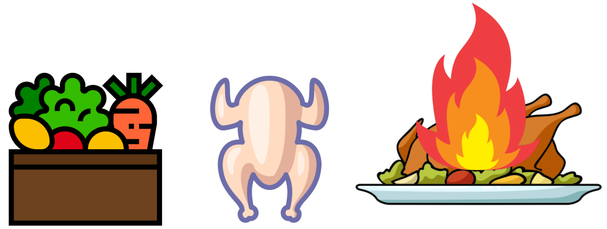
Supervised learning



Supervised Learning



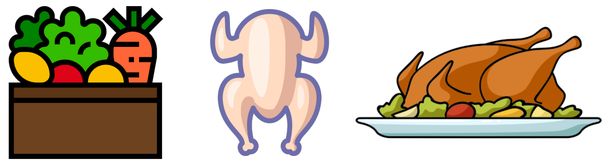
Examples



Data Label

1. Cut vegetables
2. Season chicken with lots of spice
3. Preheat oven
4. Cook chicken for 30-minutes
5. Add vegetables

Instructions



Data Label

1. Cut vegetables
2. Season chicken
3. Preheat oven
4. Cook chicken for 30-minutes
5. Add vegetables

Instructions

Supervised learning

Classification

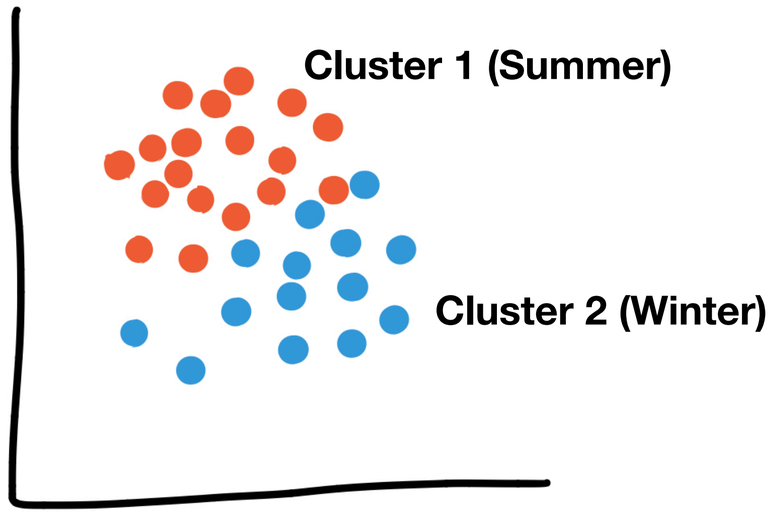
- “Is this example one thing or another?”
- Binary classification = two options
- Multi-class classification = more than two options

Regression

- “How much will this house sell for?”
- “How many people will buy this app?”

Unsupervised learning

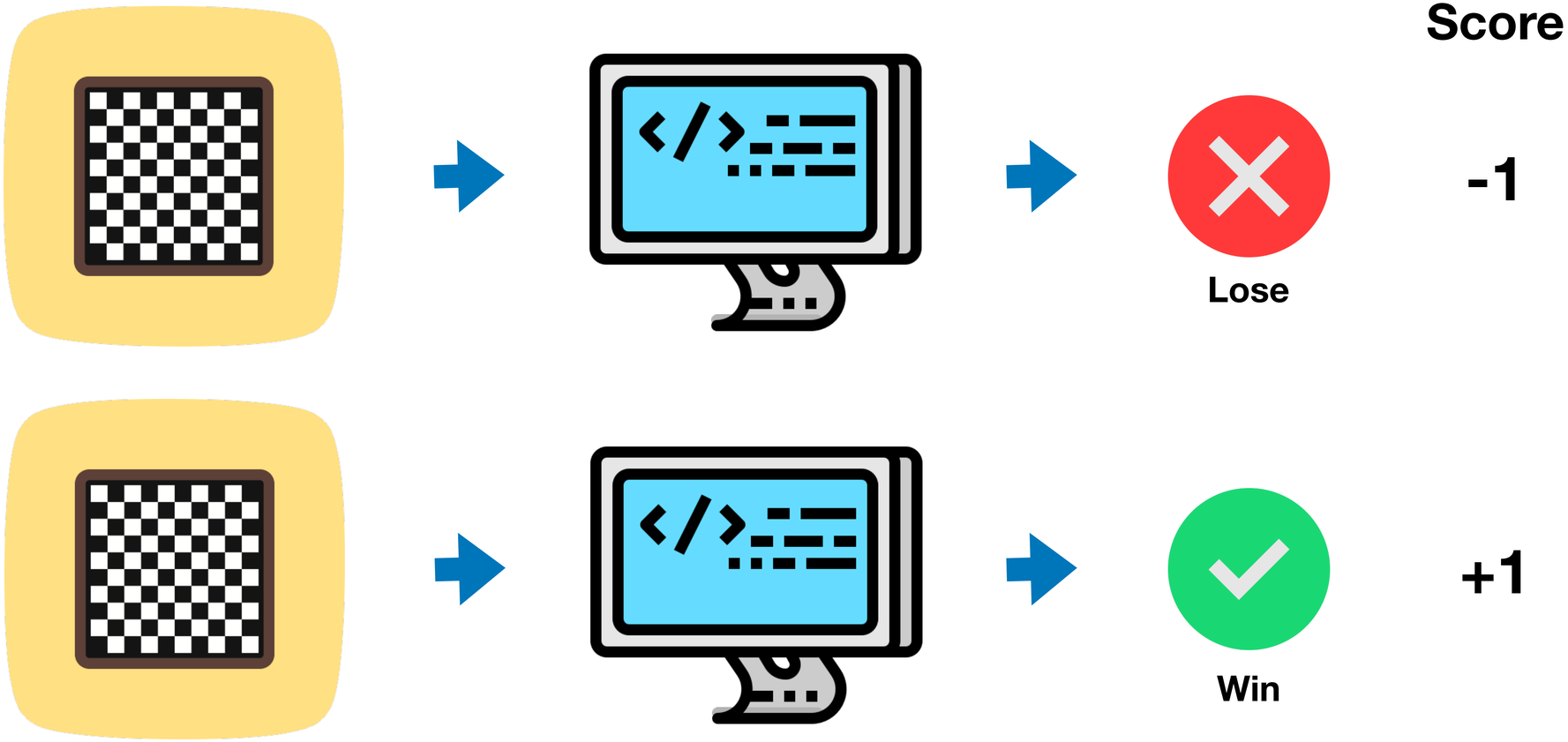
Customer ID	Purchase 1	Purchase2
1	Sunglasses	Singlet
2	Jacket	Snow boots
3	Sunscreen	Beach towel



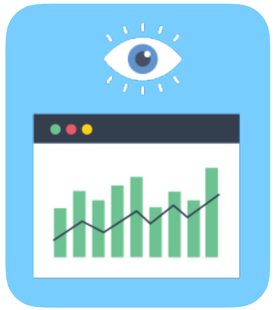
Transfer learning

Use what a model has learned in one domain, to help in another domain.

Reinforcement learning

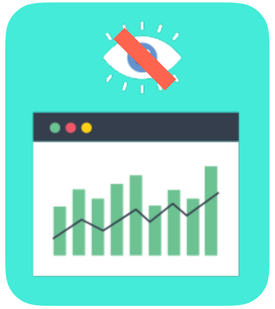


Matching your problem



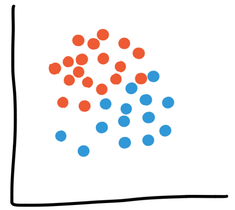
Supervised Learning

“I know my inputs and outputs.”

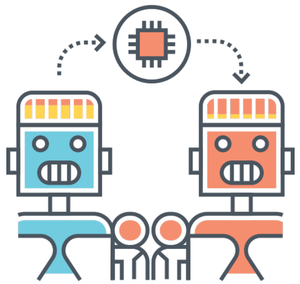


Unsupervised Learning

“I’m not sure of the outputs but I have inputs.”



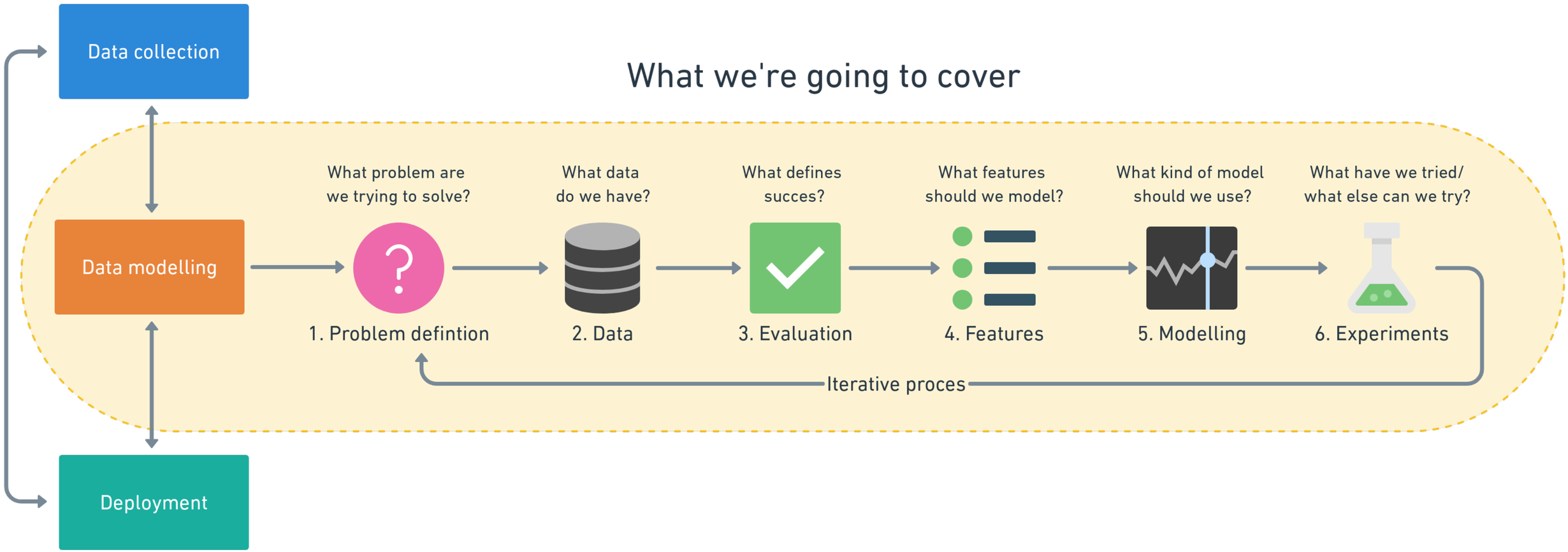
Matching your problem



Transfer Learning

“I think my problem may be similar to something else.”

Steps in a full machine learning project



2.Data 

“What kind of data do we have?”

Different types of data

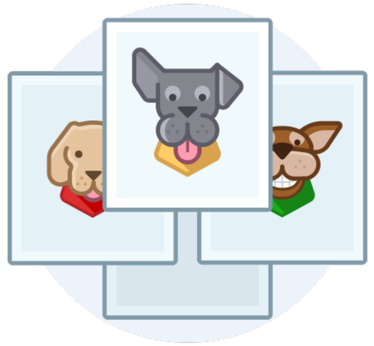
Rows

Columns

ID	Weight	Sex	Blood Pressure	Chest pain	Heart disease?
4326	110Kg	M	120/80	4	Yes
5681	64Kg	F	130/90	1	NO
7911	81Kg	M	130/80	0	NO

Table 1.0: Patient records

Structured

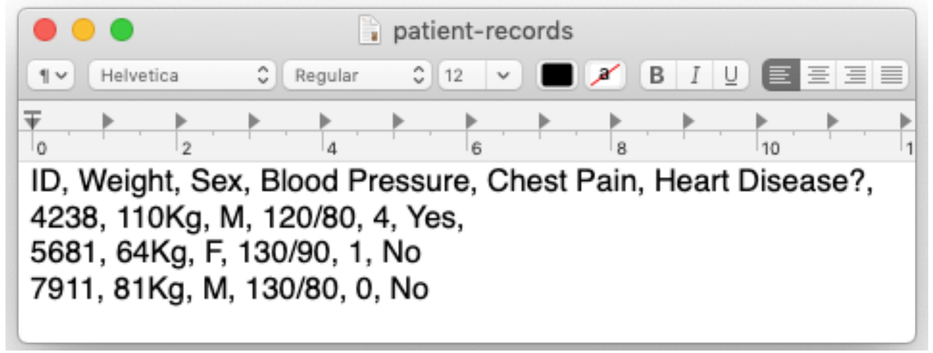


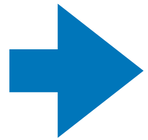
From: daniel@mrdbourke.com
Hey Daniel,

First of all, thank you for being so amazing.
This machine learning course is incredible.
Thank you for keeping it simple!

Unstructured

Different types of data





ID	Weight	Sex	Blood Pressure	Chest pain	Heart disease?
4326	110Kg	M	120/80	4	Yes
5681	64Kg	F	130/90	1	NO
7911	81Kg	M	130/80	0	NO

Table 1.0: Patient records

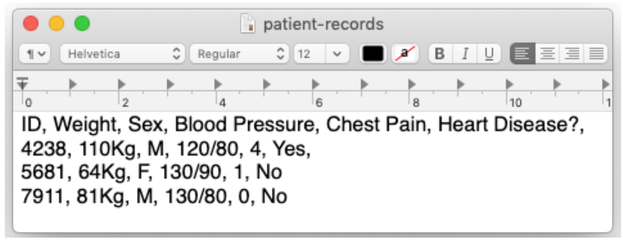
Static

“The more data the better.”

Different types of data

Streaming

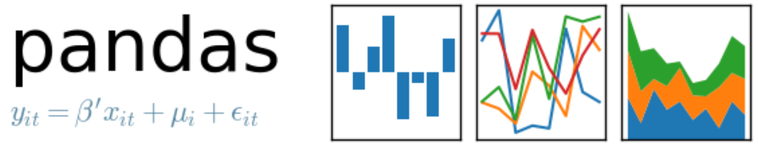
A data science workflow



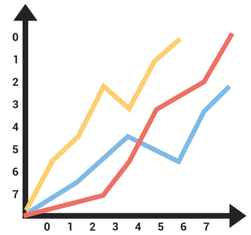
Static data

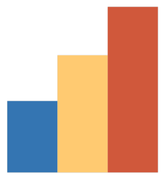
ID	Weight	Sex	Blood Pressure	Chest pain	Heart disease?
4328	110Kg	M	120/80	4	Yes
5681	64Kg	F	130/90	1	No
7911	81Kg	M	130/80	0	No

Table 1.0: Patient records



Data Analysis

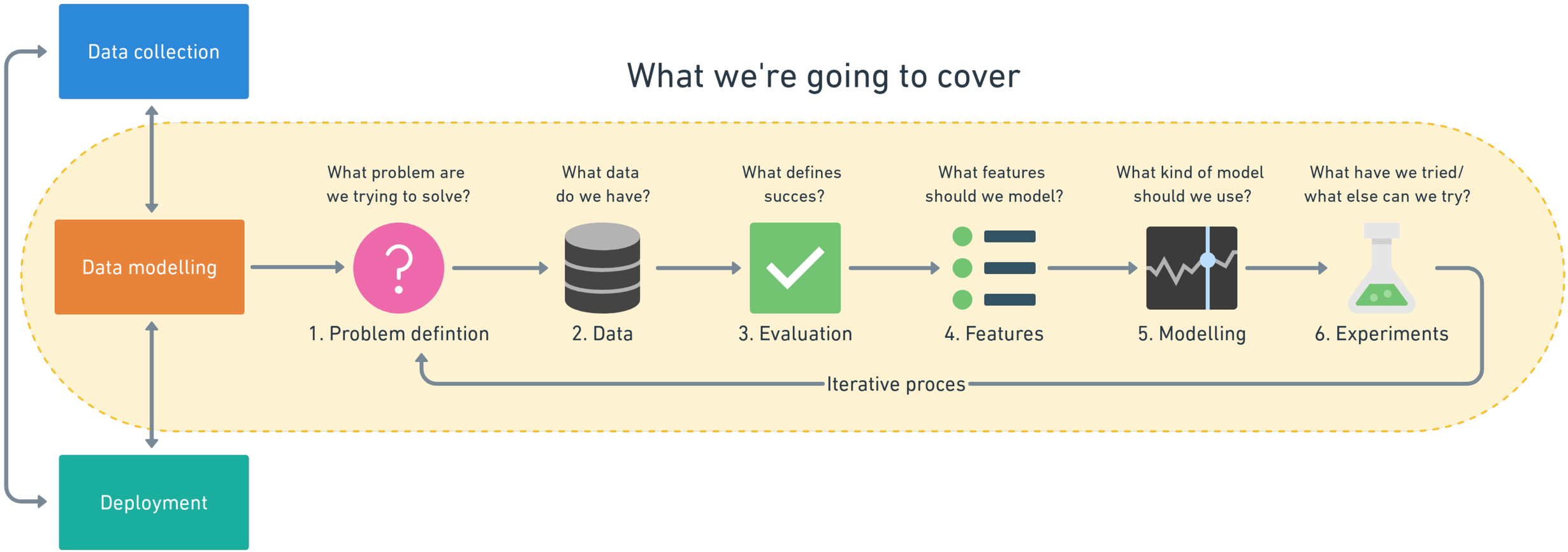




Machine learning model

What kind of data do you use?

Steps in a full machine learning project



3. Evaluation 

“What defines success for us?”

**“For this project to be worth pursuing further,
we need a machine learning model with over 99% accuracy.”**

ID	Weight	Sex	Blood Pressure	Chest pain	Heart disease?
4326	110Kg	M	120/80	4	Yes
5681	64Kg	F	130/90	1	No
7911	81Kg	M	130/80	0	No

Table 1.0: Patient records

Machine learning model

Accuracy

97.8%

Different types of metrics

Classification	Regression	Recommendation
Accuracy	Mean absolute error (MAE)	Precision at K
Precision	Mean squared error (MSE)	
Recall	Root mean squared error (RMSE)	

Classifying car insurance claims

		Data	Label
ID	Img	Text	Result
1		Hi, I crashed into the neighbours letterbox and dented my car.	At fault
2		Someone ran into the back of me whilst I was at the traffic lights.	Not at fault

Table 2.0: Car insurance claims

(had to try a few of these)

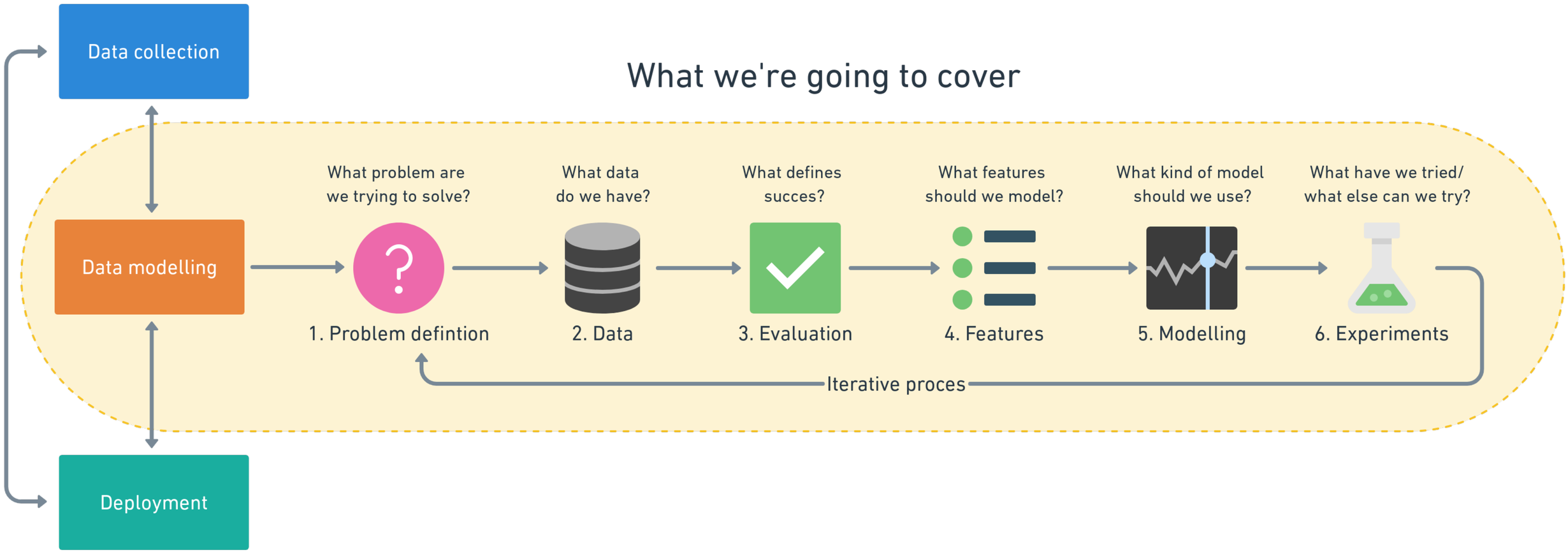
Machine learning model

Minimum accuracy

>95%

What do you measure?

Steps in a full machine learning project



4. Features 

“What do we already know about the data?”

Different features of data

Feature variables | Target variable

ID	Weight	Sex	Heart Rate	Chest pain	Heart disease?
4326	110kg	M	81	4	Yes
5681	64kg	F	61	1	NO
7911	81kg	M	57	0	NO

Table 1.0: Patient records

Different features of data

ID	Weight	Sex	Heart Rate	Chest pain	Heart disease?
4328	110Kg	M	81	4	YES
5681	64Kg	F	61	1	NO
7911	81Kg	M	57	0	NO

Table 1.0: Patient records

Numerical features

Categorical features

Different features of data

Derived feature

ID	Weight	Sex	Heart Rate	Chest pain	Heart disease?	visit in last year?
4326	110Kg	M	81	4	Yes	Yes
5681	64Kg	F	61	1	NO	Yes
7911	81Kg	M	57	0	NO	NO

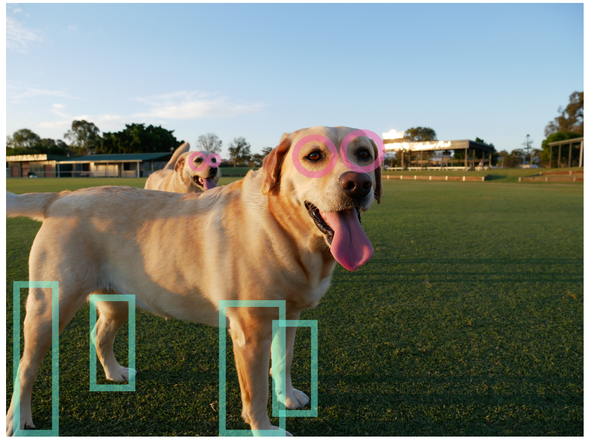
Table 1.0: Patient records

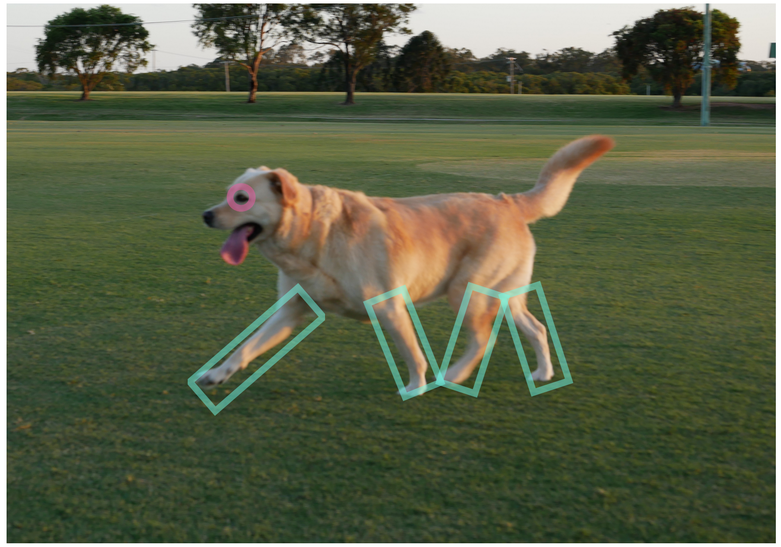
Numerical features

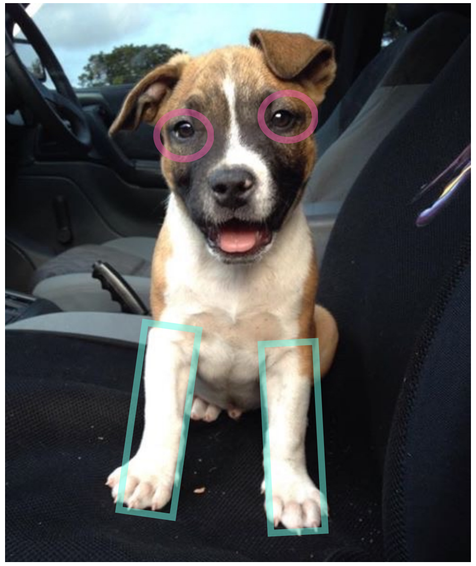
Categorical features

Feature engineering Looking at different features of data and creating new ones/altering existing ones

Different features of data







What features should you use?

ID	Weight	Sex	Heart Rate	Chest pain	Heart disease?	ost eaten food
4326	110Kg	M	81	4	YES	ries
5681	64Kg	F	61	1	NO	?
7911	81Kg	M	57	0	NO	?

Table 1.0: Patient records

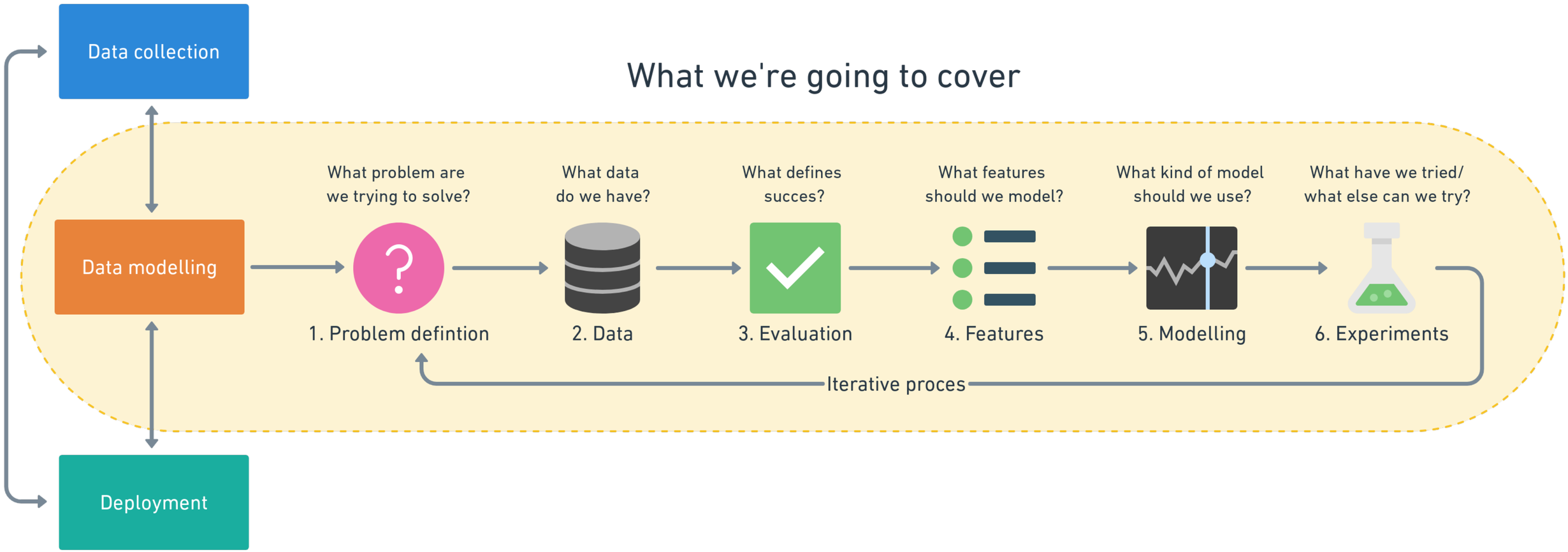
Want > 10% coverage

Feature coverage

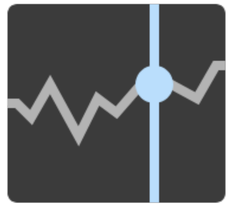
How many samples have different features? Ideally, every sample has the same features.

What are features of your problems?

Steps in a full machine learning project



5. Modelling Part 1 — 3 sets



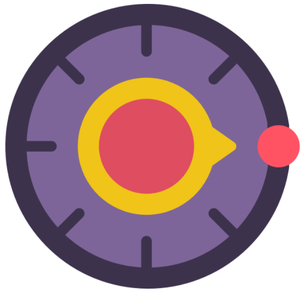
“Based on our problem and data, what model should we use?”

3 parts to modelling

1. Choosing and training a model

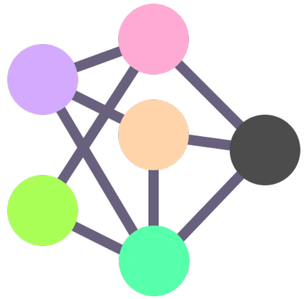
or

2. Tuning a model



3. Model comparison

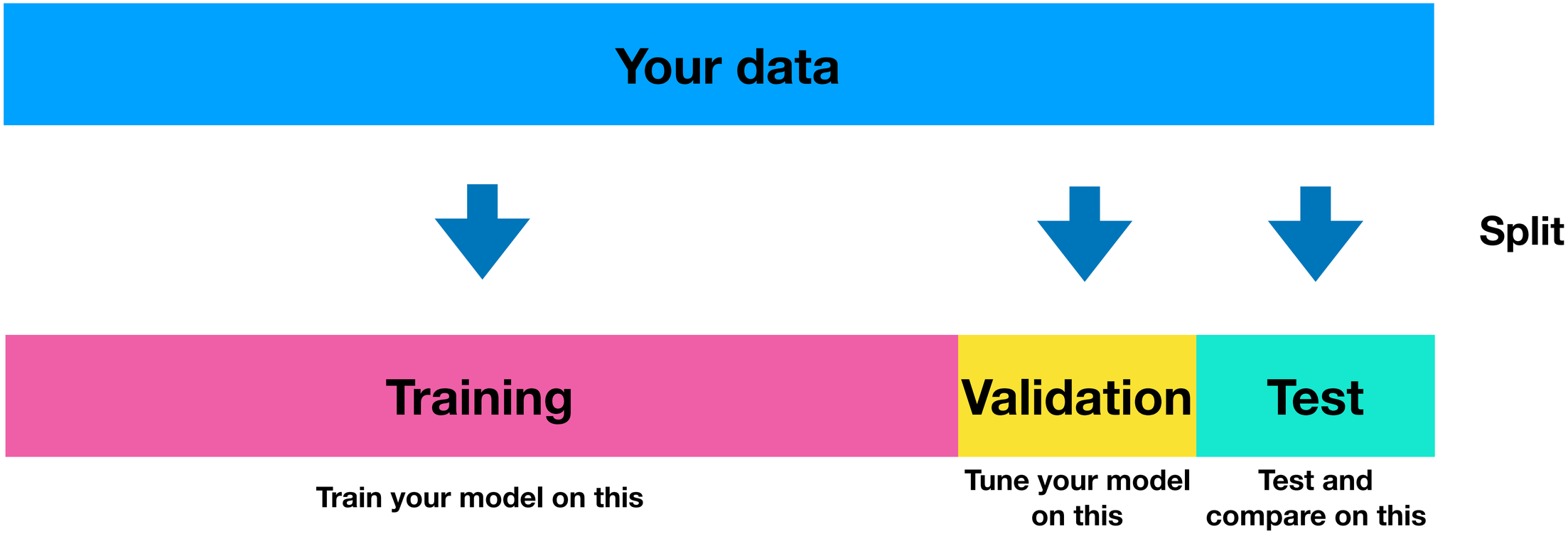
vs.



vs.

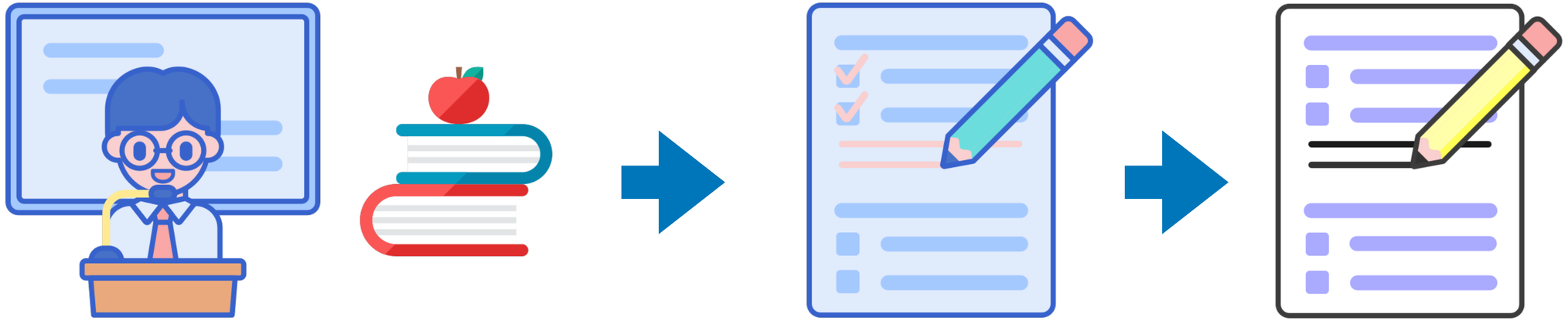
The most important concept in machine learning

(the training, validation and test sets or 3 sets)



The most important concept in machine learning

(the 3 sets)



Course materials (training set)

Practice exam (validation set)

Final exam (test set)

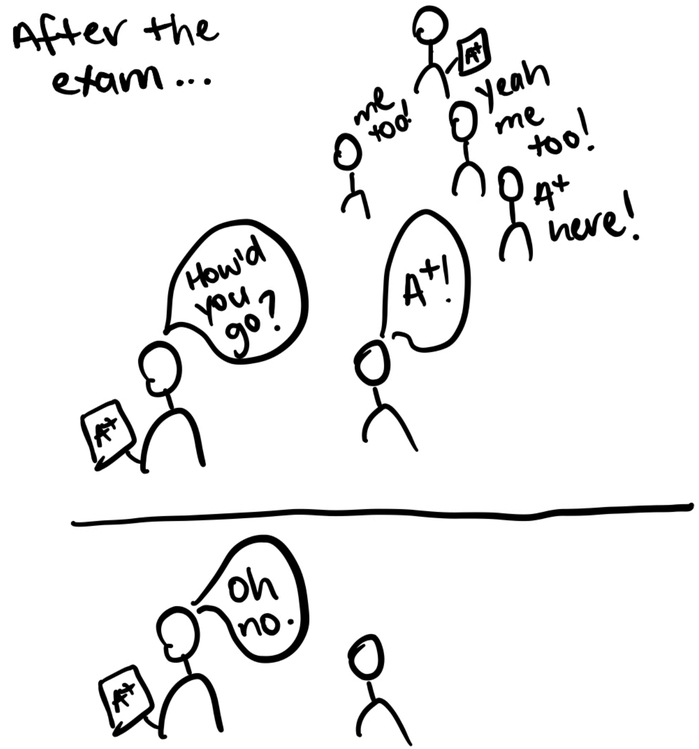
Generalization

The ability for a machine learning model to perform well on data it hasn't seen before.

When things go wrong

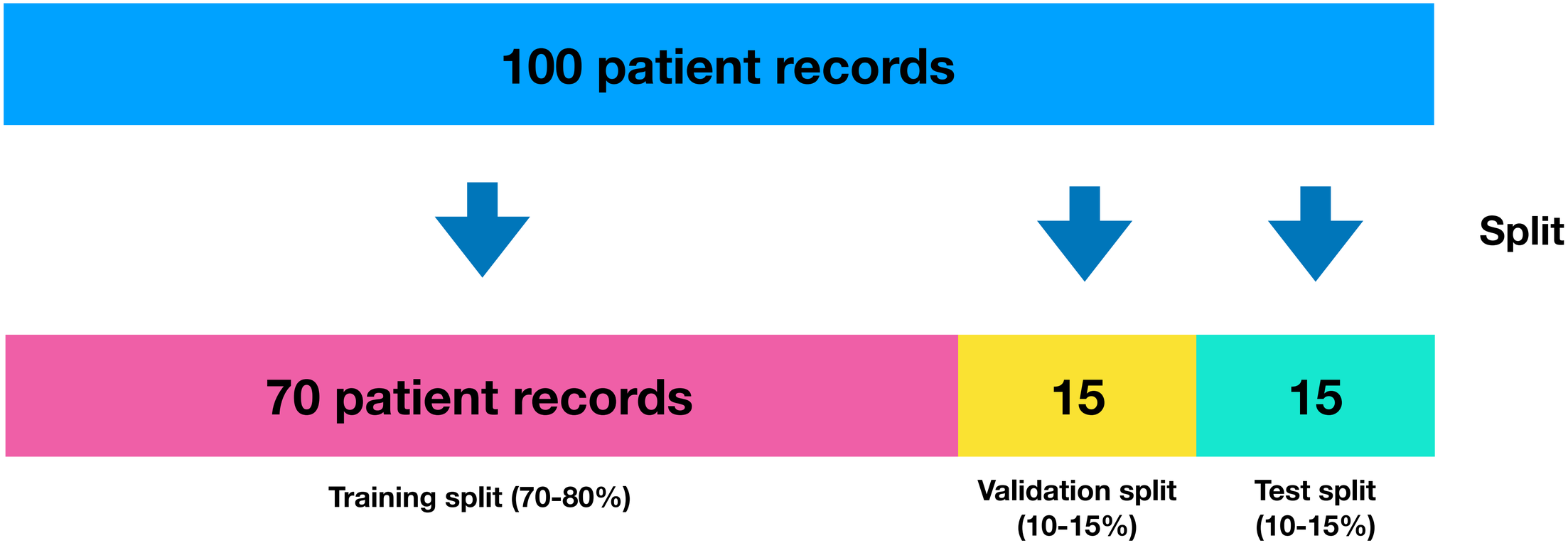
Practice exam
(same as final exam set)

Final exam
(already seen it)



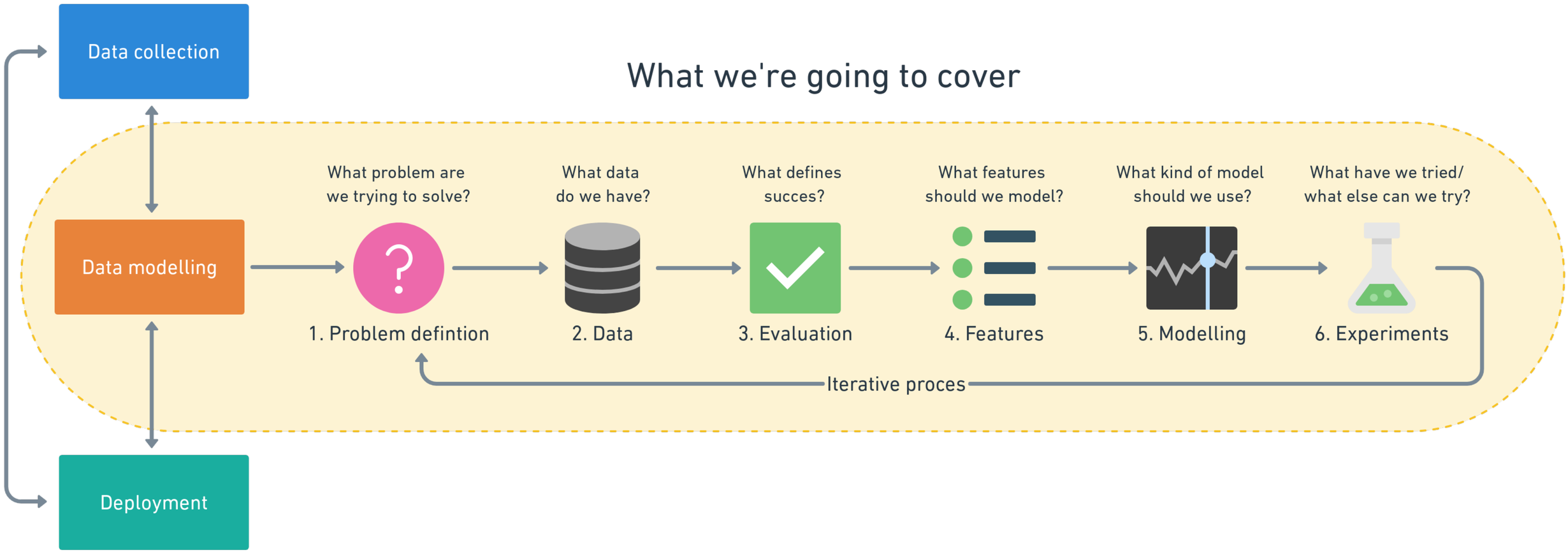
The most important concept in machine learning

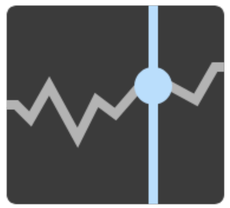
(the 3 sets)



What was the last thing you testing your ability on?

Steps in a full machine learning project



5. Modelling Part 2 — Choosing 

“Based on our problem and data, what model should we use?”

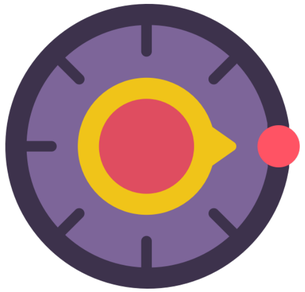
3 parts to modelling

1. Choosing and training a model

or

Training Data

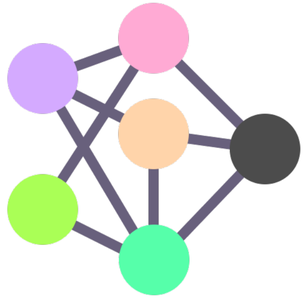
2. Tuning a model



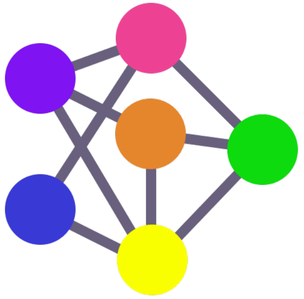
Validation Data

3. Model comparison

vs.



vs.



Test Data

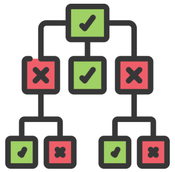
Choosing a model

Problem 1

Model 1

Structured Data

CatBoost



Random Forest

Problem 2

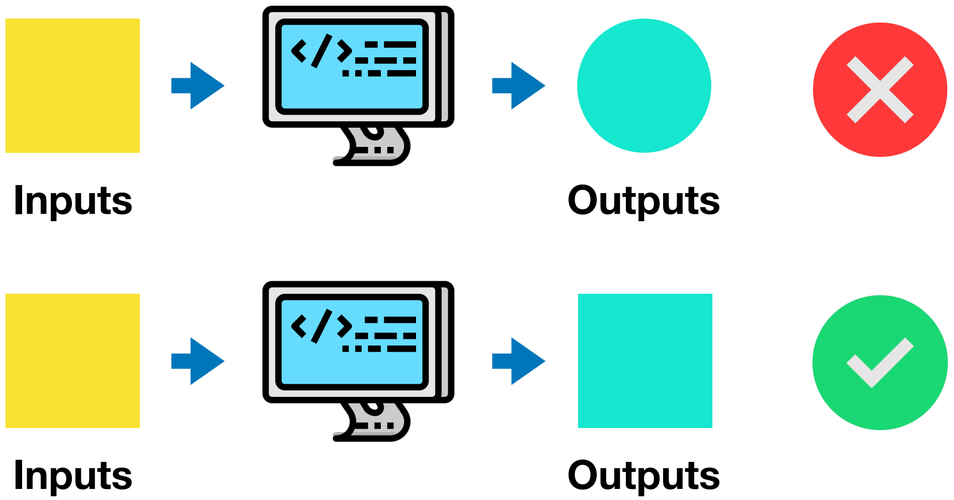
Model 2

Unstructured Data

Deep Learning

Transfer Learning

Training a model



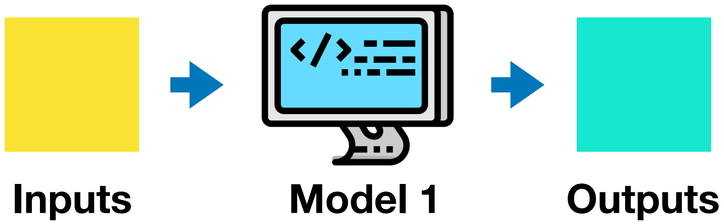
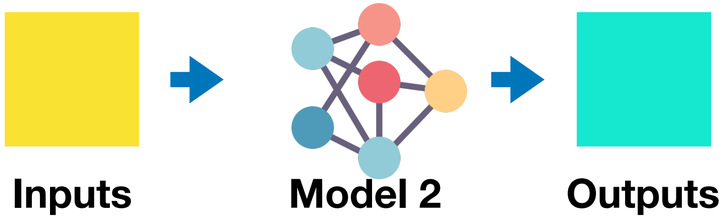
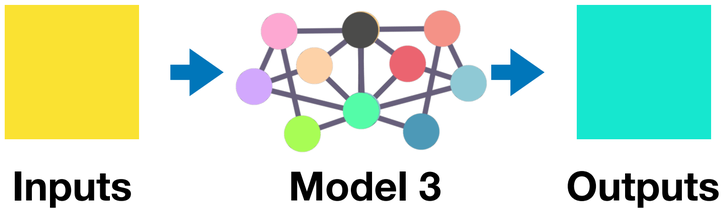
X (data) y (label)

ID	Weight	Sex	Heart Rate	Chest pain	Heart disease?
4326	110kg	M	81	4	YES
5681	64kg	F	61	1	NO
7911	81kg	M	57	0	NO

Table 1.0: Patient records

Training Data

Goal: Minimise time between experiments

Experiment		Accuracy	Training time
1		87.5%	3 min
2		91.3%	92 min
3		94.7%	176 min

Things to remember

- Some models work better than others on different problems
- Don’t be afraid to try things
- Start small and build up (add complexity) as you need

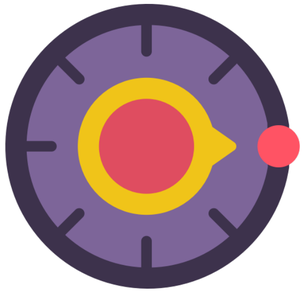
Up next

1. Choosing and training a model

or

Training Data

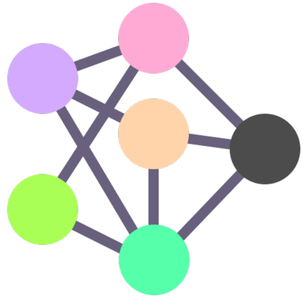
2. Tuning a model



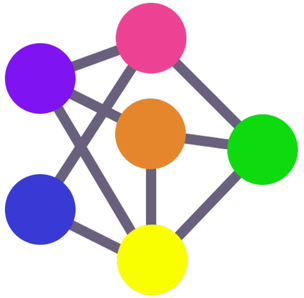
Validation Data

3. Model comparison

vs.

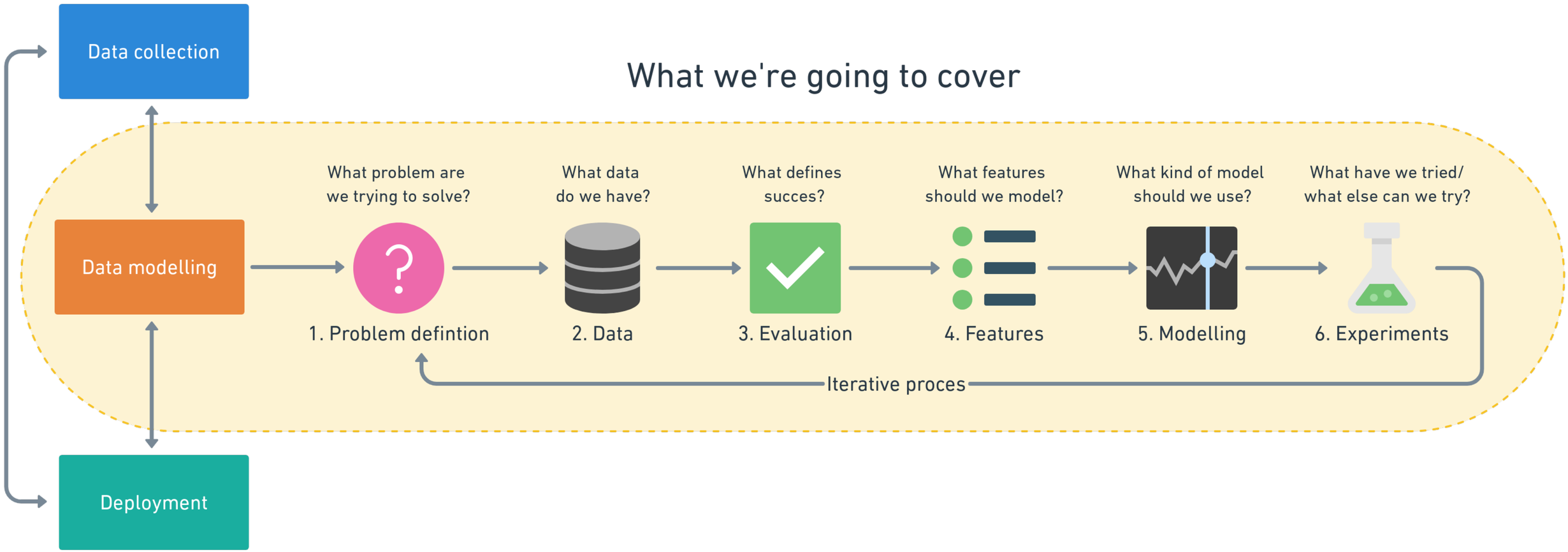


vs.

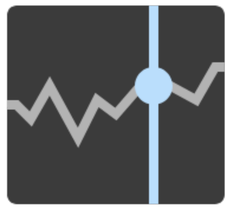


Test Data

Steps in a full machine learning project



5. Modelling Part 3 — Tuning



“Based on our problem and data, what model should we use?”

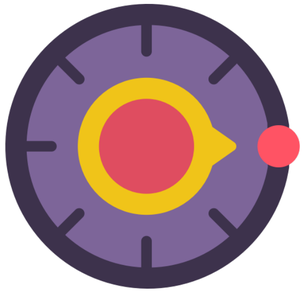
3 parts to modelling

1. Choosing and training a model

or

Training Data

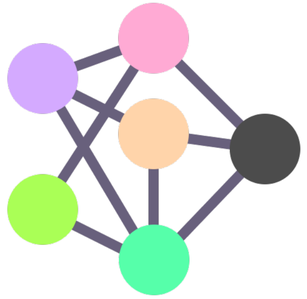
2. Tuning a model



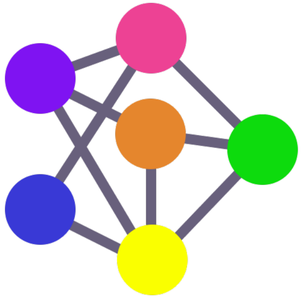
Validation Data

3. Model comparison

vs.



vs.



Test Data

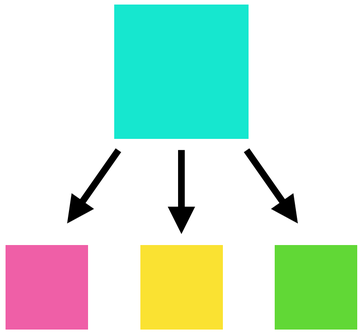
Tuning a model

Cooking time: 1 hour
Temperature: 180ºC

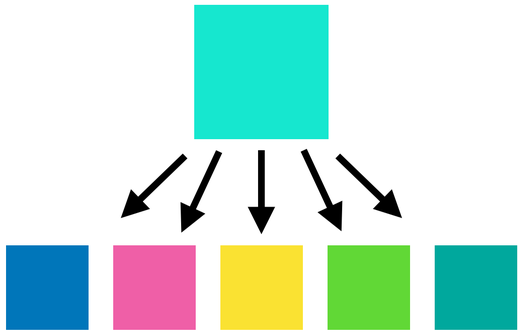
Cooking time: 1 hour
Temperature: 200ºC

Tuning a model

Random Forest

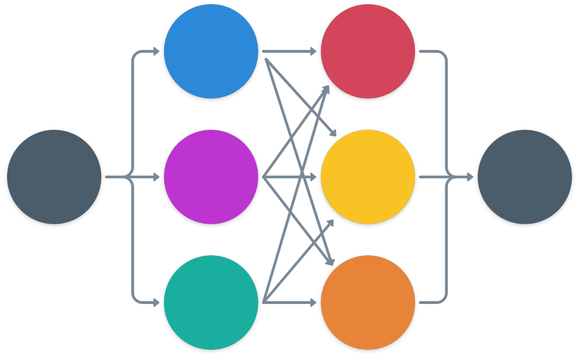


3 trees

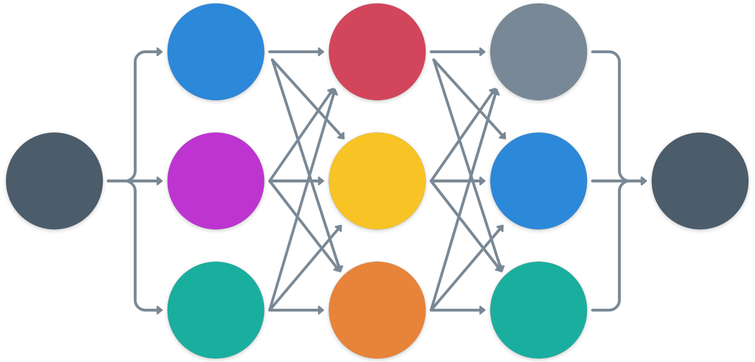


5 trees

Neural Networks



2 layers



3 layers

Things to remember

- Machine learning models have hyperparameters you can adjust
- A models first results aren’t its last
- Tuning can take place on training or validation data sets

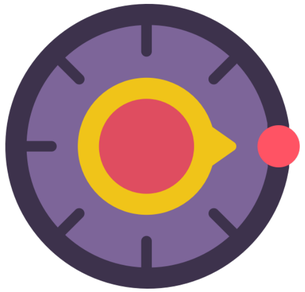
Up next

1. Choosing and training a model

or

Training Data

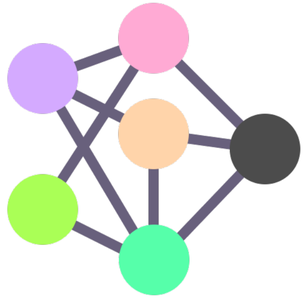
2. Tuning a model



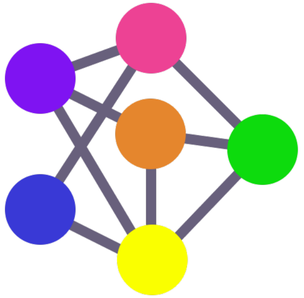
Validation Data

3. Model comparison

vs.

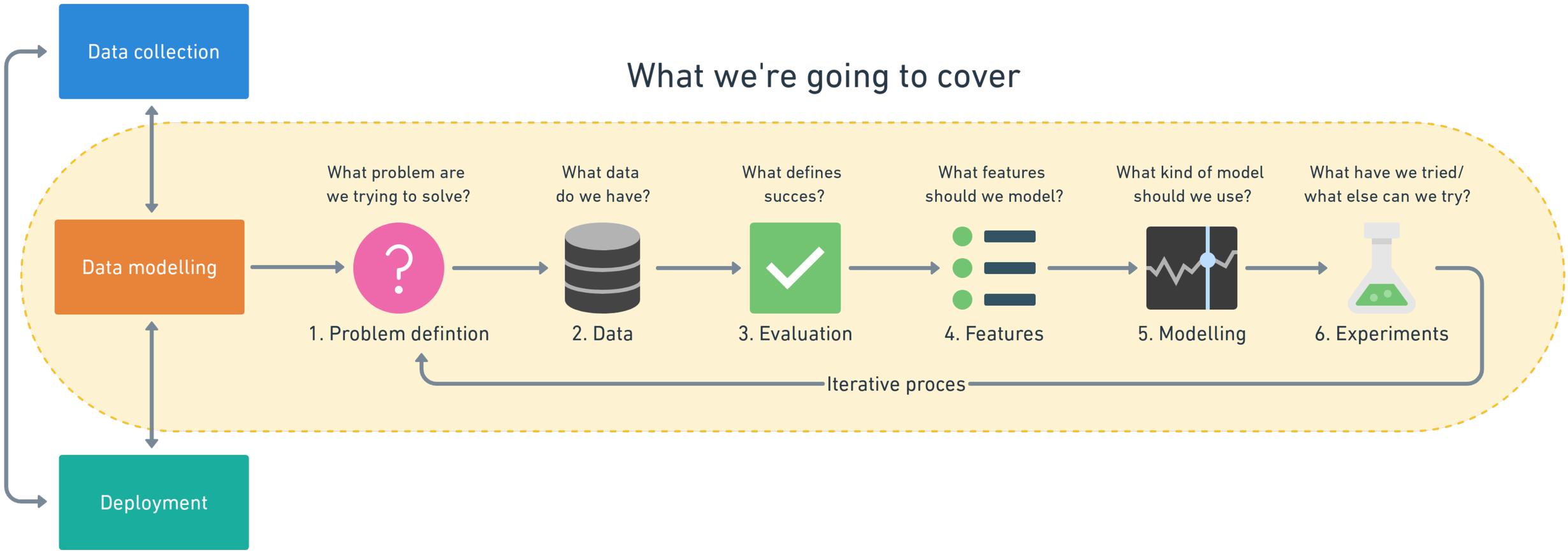


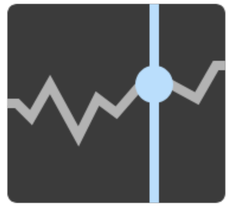
vs.



Test Data

Steps in a full machine learning project





5. Modelling Part 4 — Comparison

“How will our model perform in the real world?”

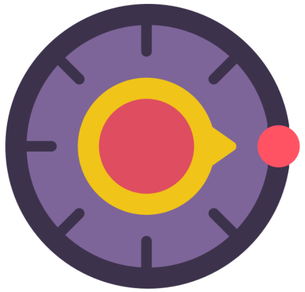
3 parts to modelling

1. Choosing and training a model

or

Training Data

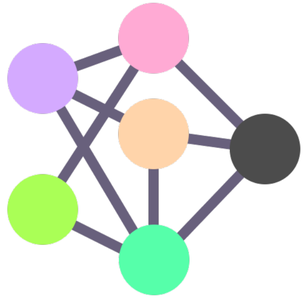
2. Tuning a model



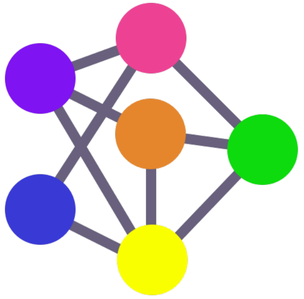
Validation Data

3. Model comparison

vs.



vs.



Test Data

Testing a model

Data Set	Performance
Training	98%
Test	96%

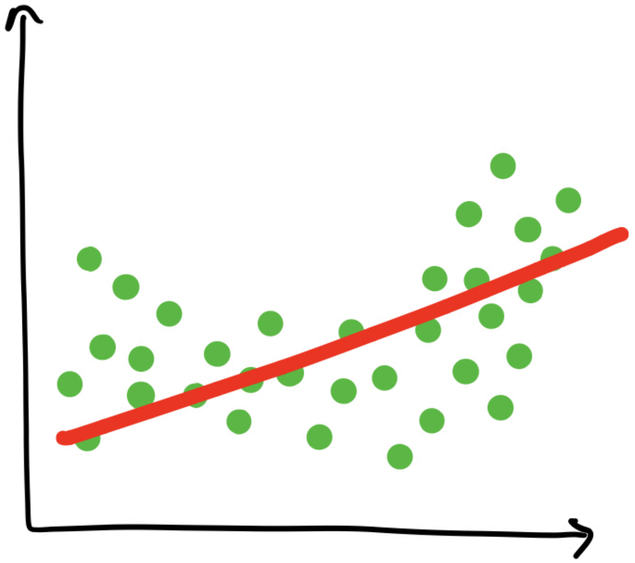
Underfitting (potential)

Data Set	Performance
Training	64%
Test	47%

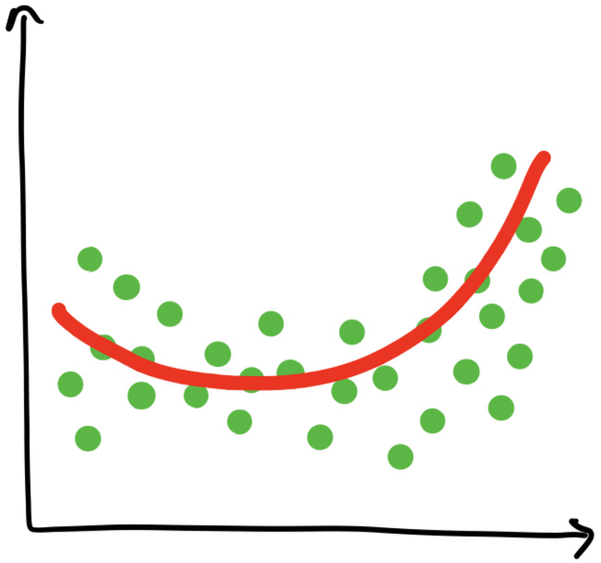
Overfitting (potential)

Data Set	Performance
Training	93%
Test	99%

Overfitting and underfitting

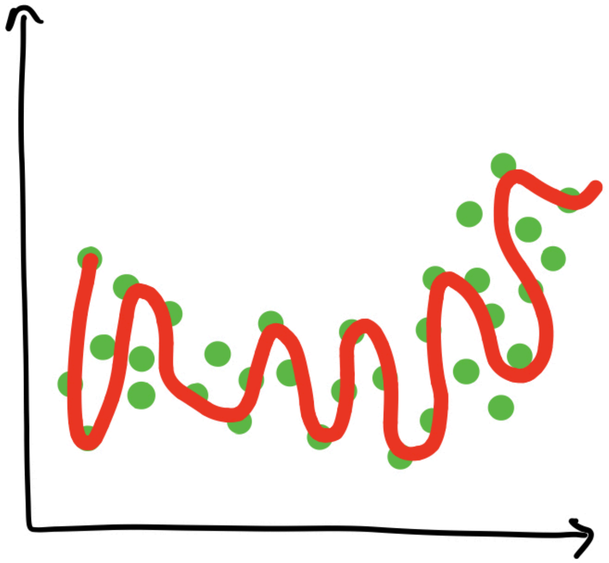


Underfitting



Balanced

(Goldilocks zone)

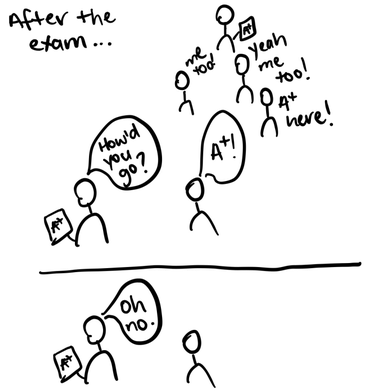


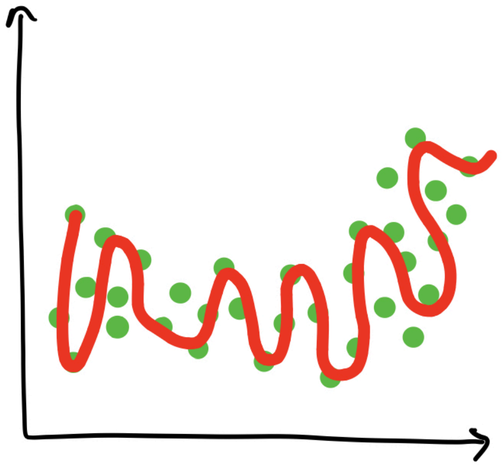
Overfitting

Overfitting and underfitting

Practice exam

Final exam





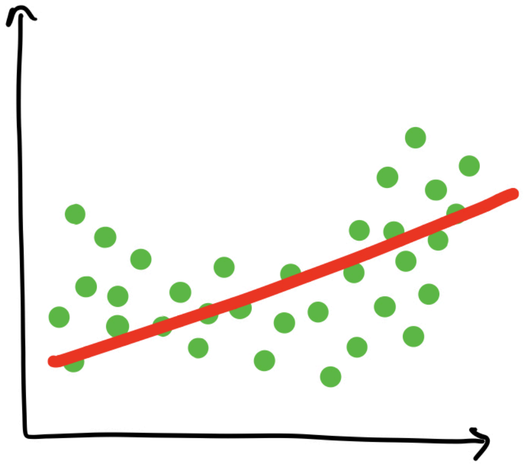
Overfitting

Data leakage

Overfitting and underfitting

Training Data

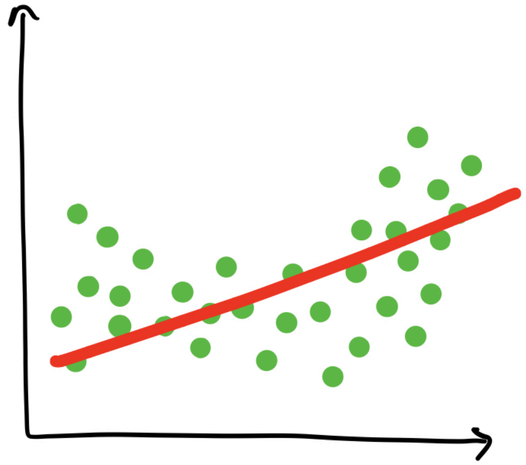
Test Data



Data mismatch

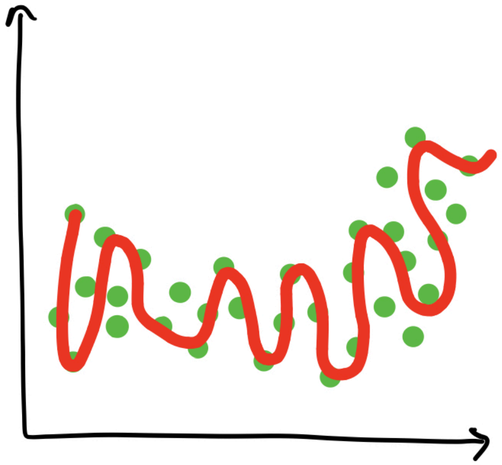
Underfitting

Fixes for overfitting and underfitting



Underfitting

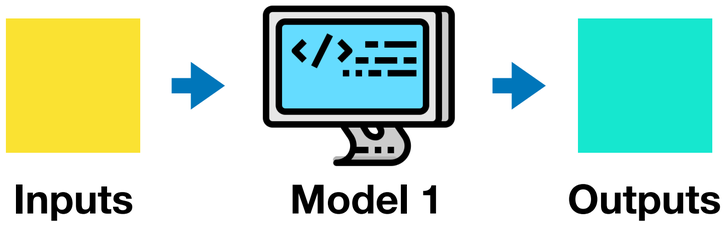
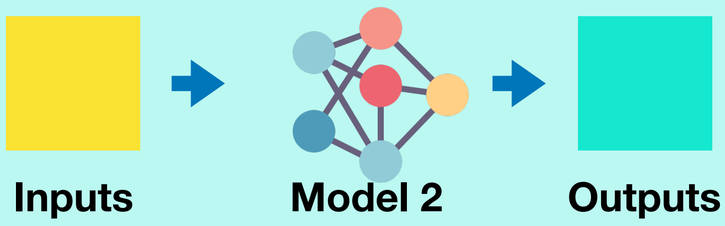
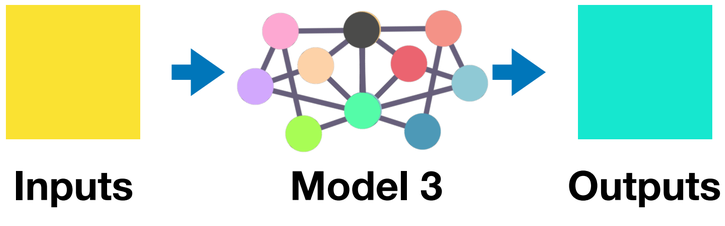
- Try a more advanced model
- Increase model hyperparameters
- Reduce amount of features
- Train longer



Overfitting

- Collect more data
- Try a less advanced model

Comparing models

Experiment		Accuracy	Training time	Prediction time
1		87.5%	3 min	0.5 sec
2		91.3%	92 min	1 sec
3		94.7%	176 min	4 sec

Things to remember

- **Want to avoid overfitting and underfitting (head towards generality)**
- **Keep the test set separate at all costs**
- **Compare apples to apples**
- **One best performance metric does not equal best model**

Before we get into the experimentation side of things, it's worth having a little reminder of overfitting and underfitting are.

All experiments should be conducted on different portions of your data.

Training data set Use this set for model training, 7080% of your data is the standard.

Validation/development data set Use this set for model hyperparameter tuning and experimentation evaluation, 1015% of your data is the standard.

Test data set Use this set for model testing and comparison, 1015% of your data is the standard.

These amounts can fluctuate slightly, depending on your problem and the data you have.

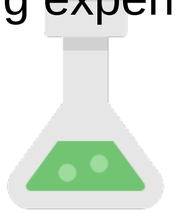
Poor performance on training data means the model hasnt learned properly and is underfitting. Try a different model, improve the existing one through hyperparameter or collect more data.

Great performance on the training data but poor performance on test data means your model doesnt generalize well. Your model may be overfitting the training data. Try using a simpler model or making sure your the test data is of the same style your model is training on.

Up next

Another form of overfitting can come in the form of better performance on test data than training data. This may mean your testing data is leaking into your training data (incorrect data splits) or you've spent too much time optimizing your model for the test set data. Ensure your training and test datasets are kept separate at all times and avoid optimizing a models performance on the test set (use the training and validation sets for model improvement).
Poor performance once deployed (in the real world) means theres a difference in what you trained and tested your model on and what is actually happening. Ensure the data you're using during experimentation matches up with the data you're using in production.

6. Experimentation

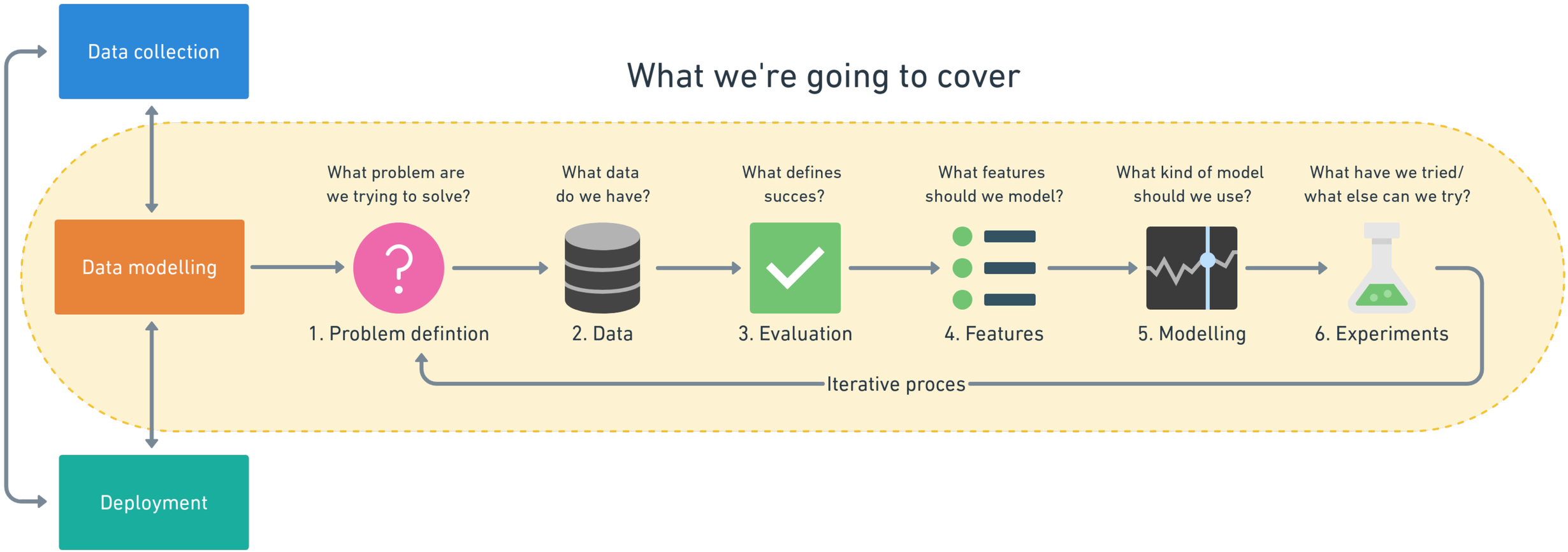


“How could we improve/what can we try next?”

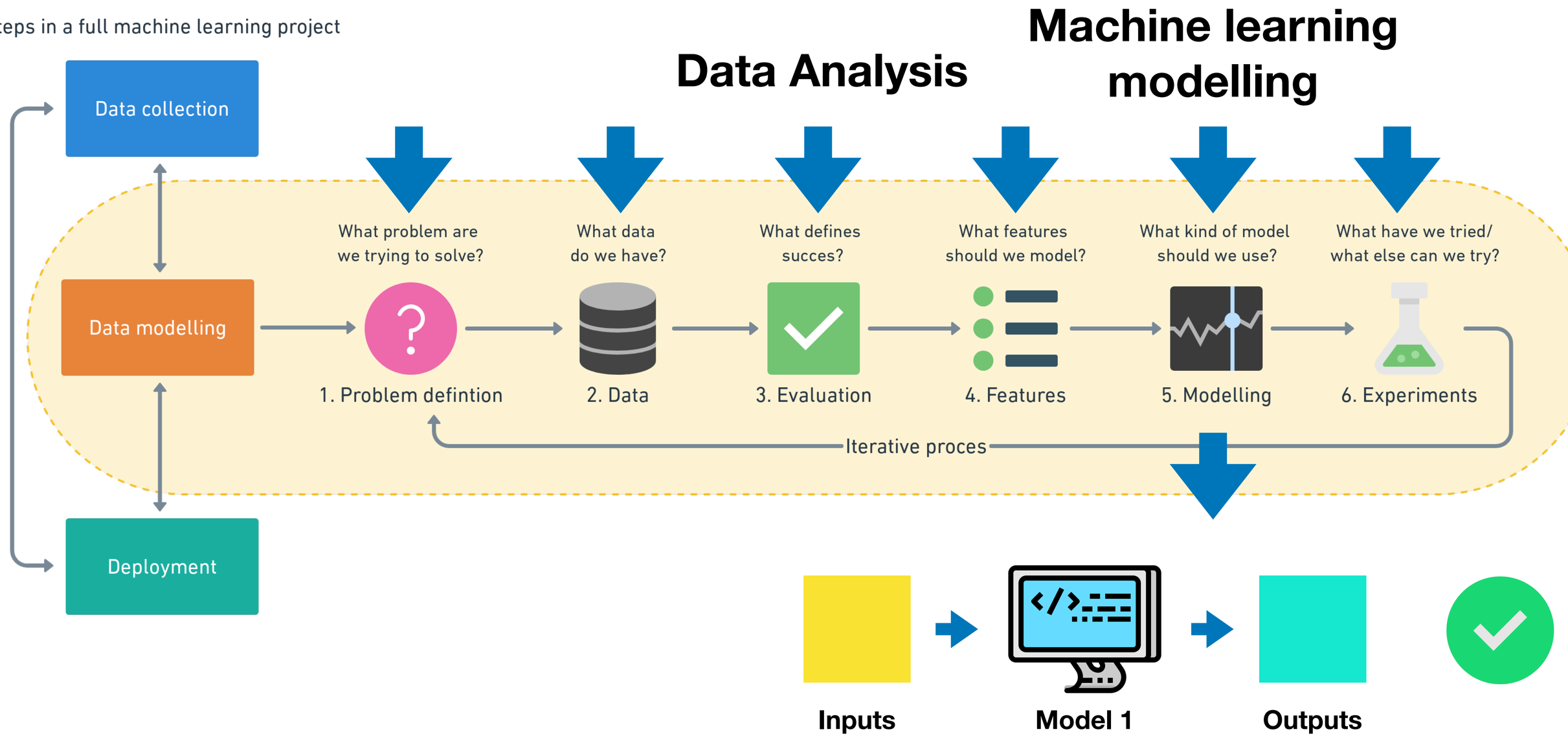
6. Experimentation 

“How could we improve/what can we try next?”

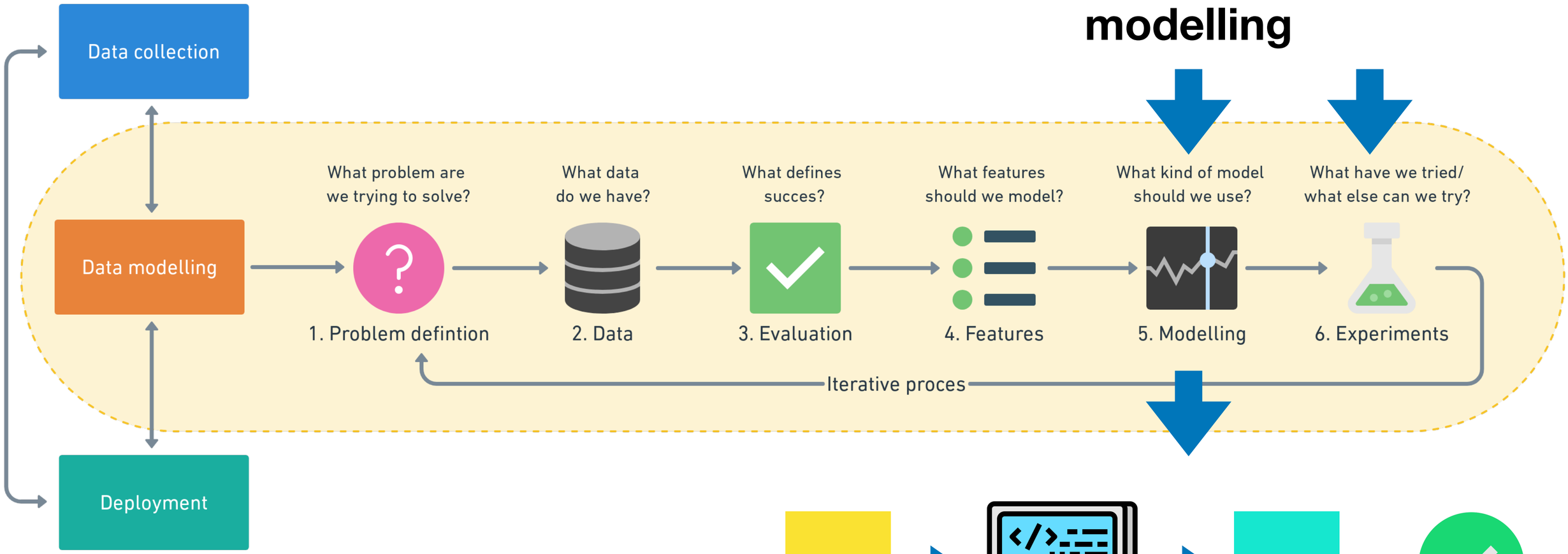
Steps in a full machine learning project



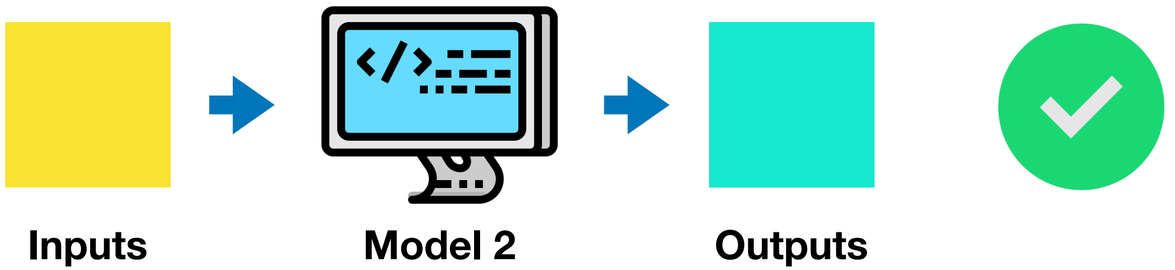
Steps in a full machine learning project



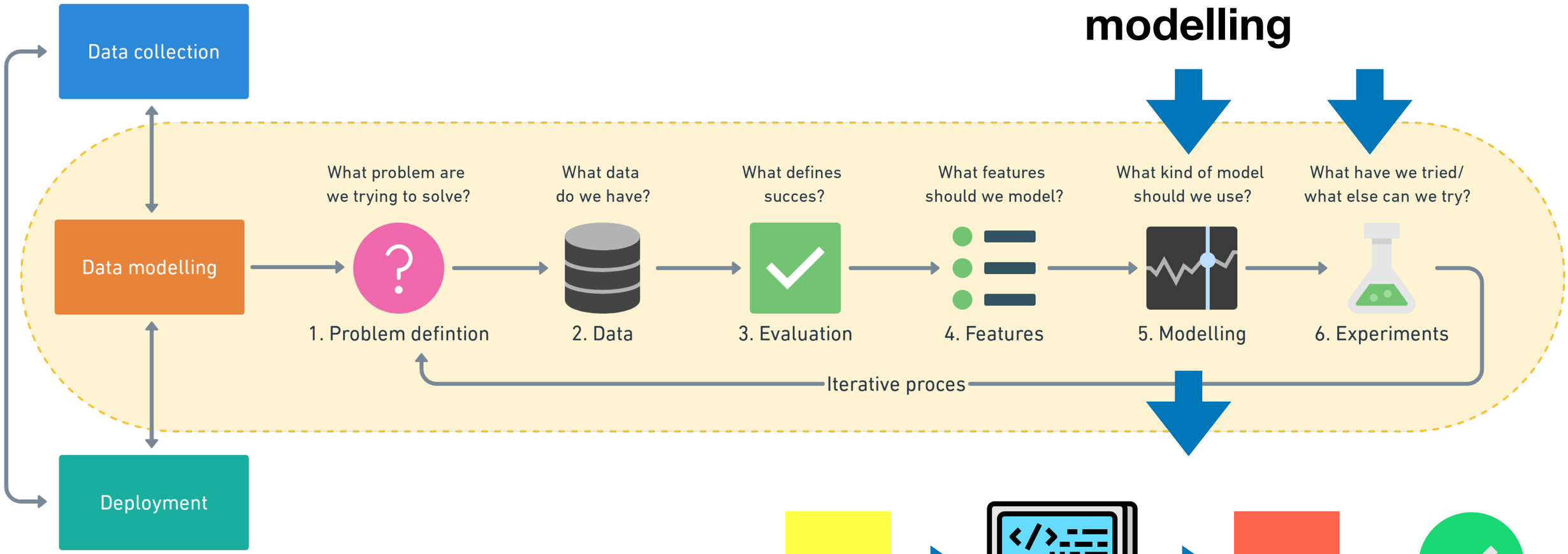
Steps in a full machine learning project



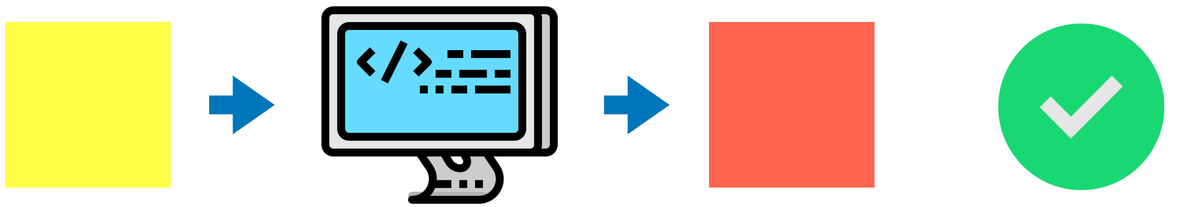
Machine learning modelling



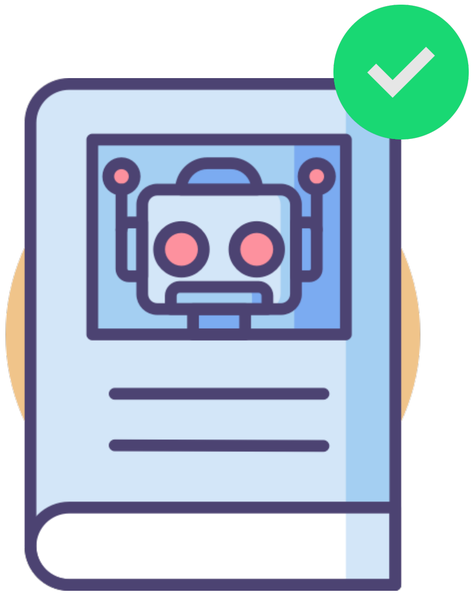
Steps in a full machine learning project



Machine learning modelling



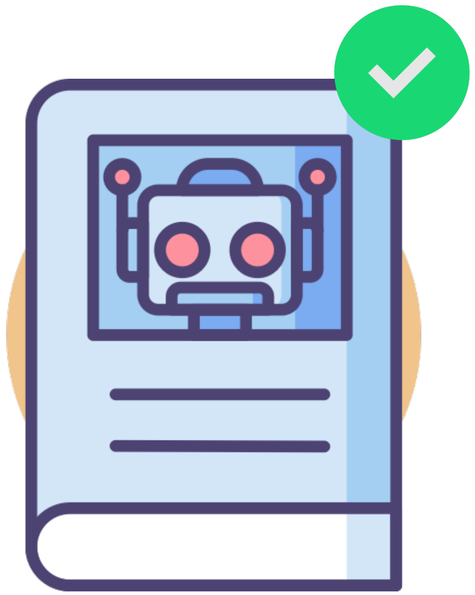
Up next

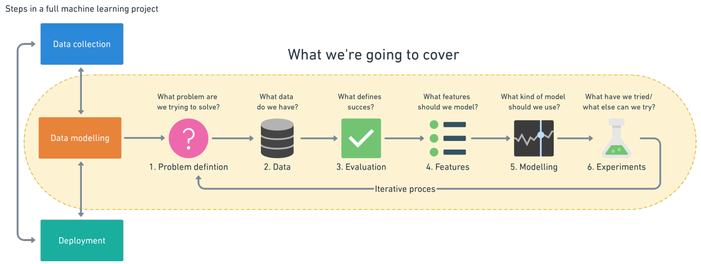


1. Create a framework

2. Match to data science and machine learning tools

3. Learn by doing



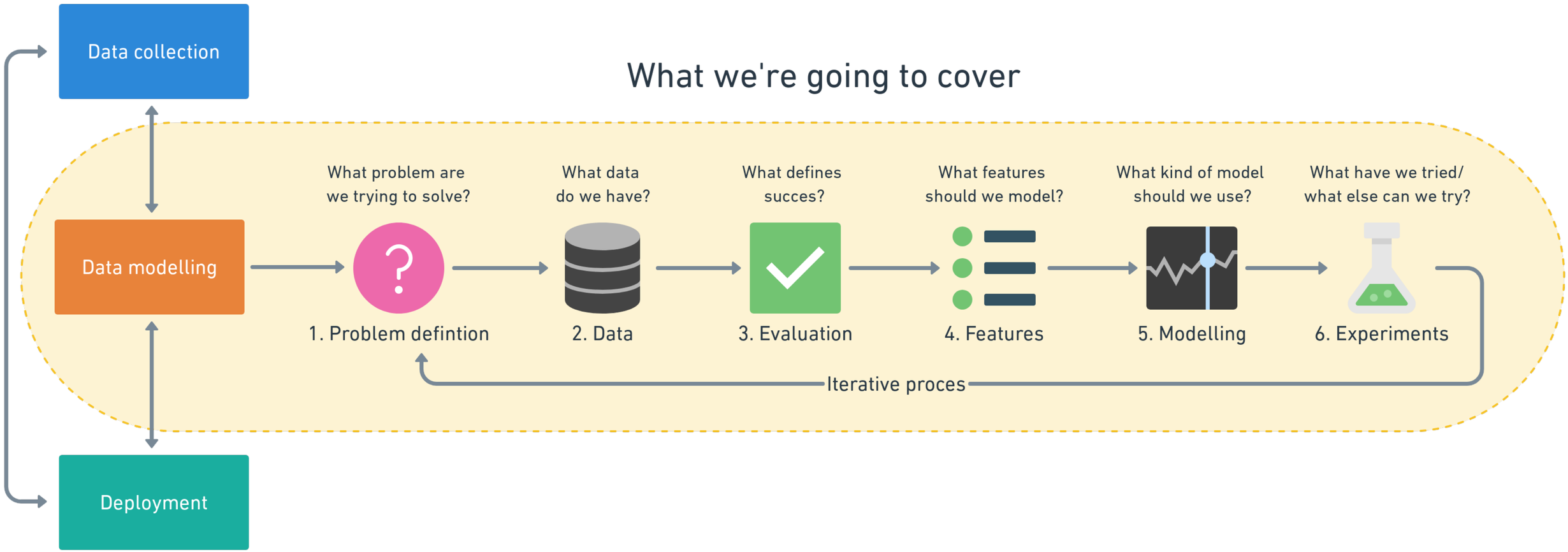


1. Create a framework

2. Match to data science and machine learning tools

3. Learn by doing

Steps in a full machine learning project



Your computer

ANACONDA

jupyter

matplotlib

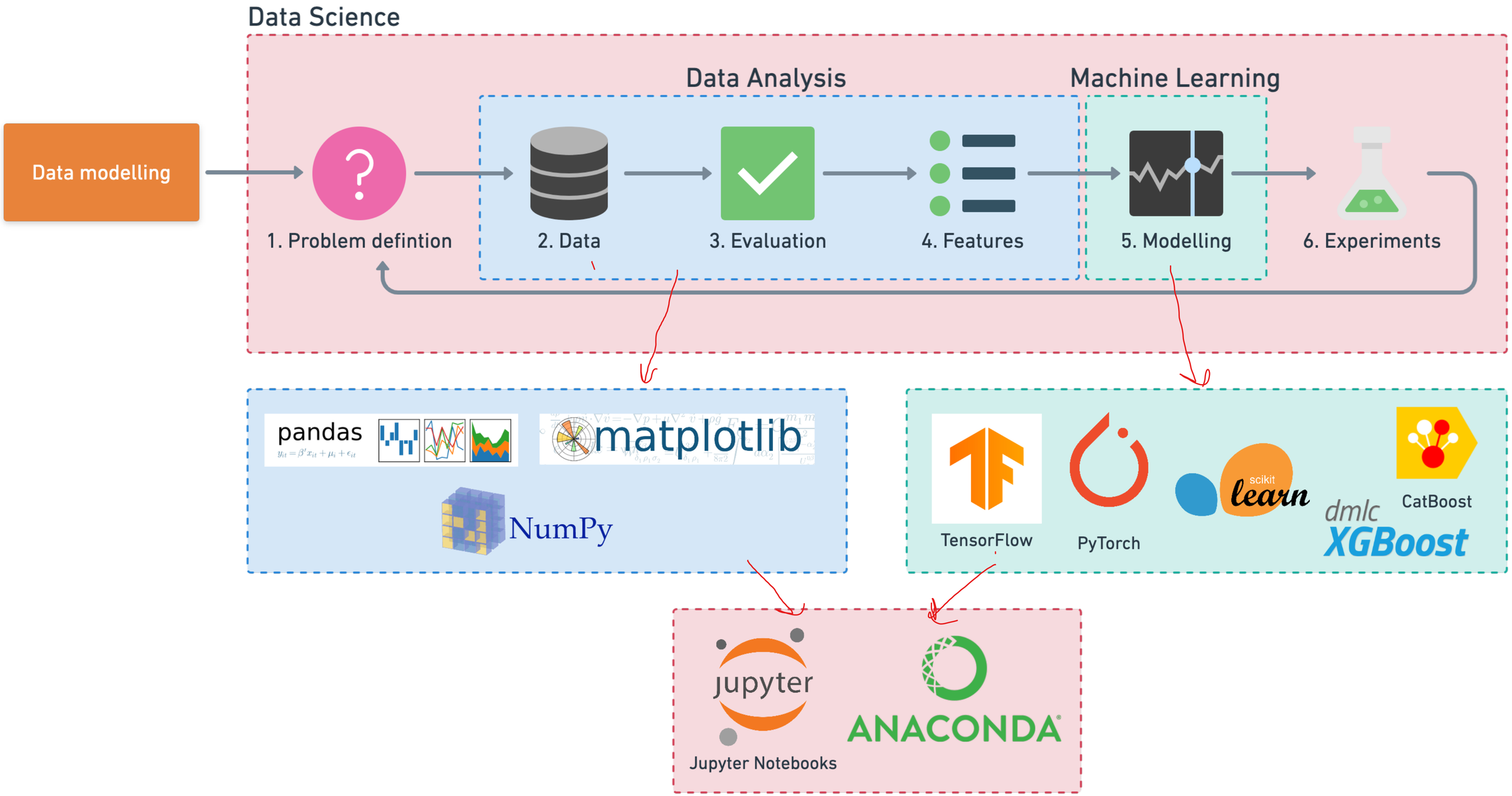
NumPy

pandas

scikit learn

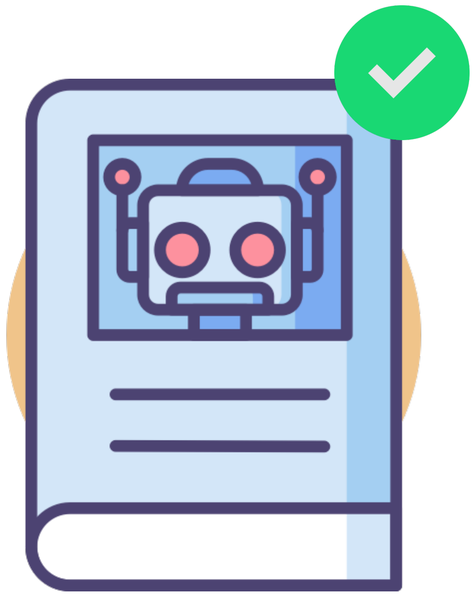
dmlc XGBoost

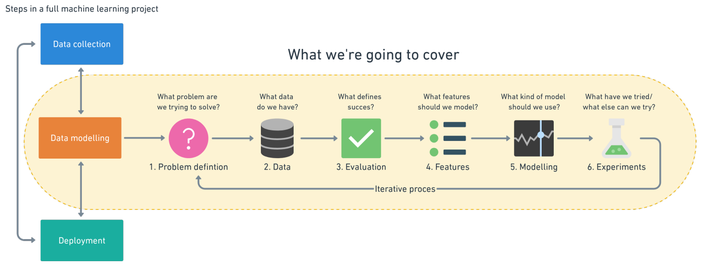
Tools you can use



Up next

Massive effort getting through the first section! There was a lot to go through and if you're thinking, "wow this is too much...", don't worry, you're not alone.
Machine learning is broad and learning a new skill takes time.
One place you might want to check out for some auxiliary learning whilst you go through the rest of this course is the Elements of AI website.
It's got some great introductory explanations of many of the concepts involved in machine learning, data science and artificial intelligence.
Of course, going through the Elements of AI material is completely optional. But if you need a break from coding (we'll be doing plenty of it), remember it's always there.
Now you've had an introduction to machine learning, let's get your computer set up for it!





1. Create a framework

2. Match to data science and machine learning tools

3. Learn by doing

Your computer

ANACONDA®

MINICONDA®

CONDA®

jupyter

matplotlib

NumPy

pandas

scikit learn

dmlc XGBoost

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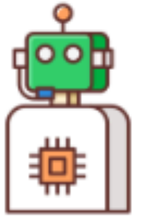
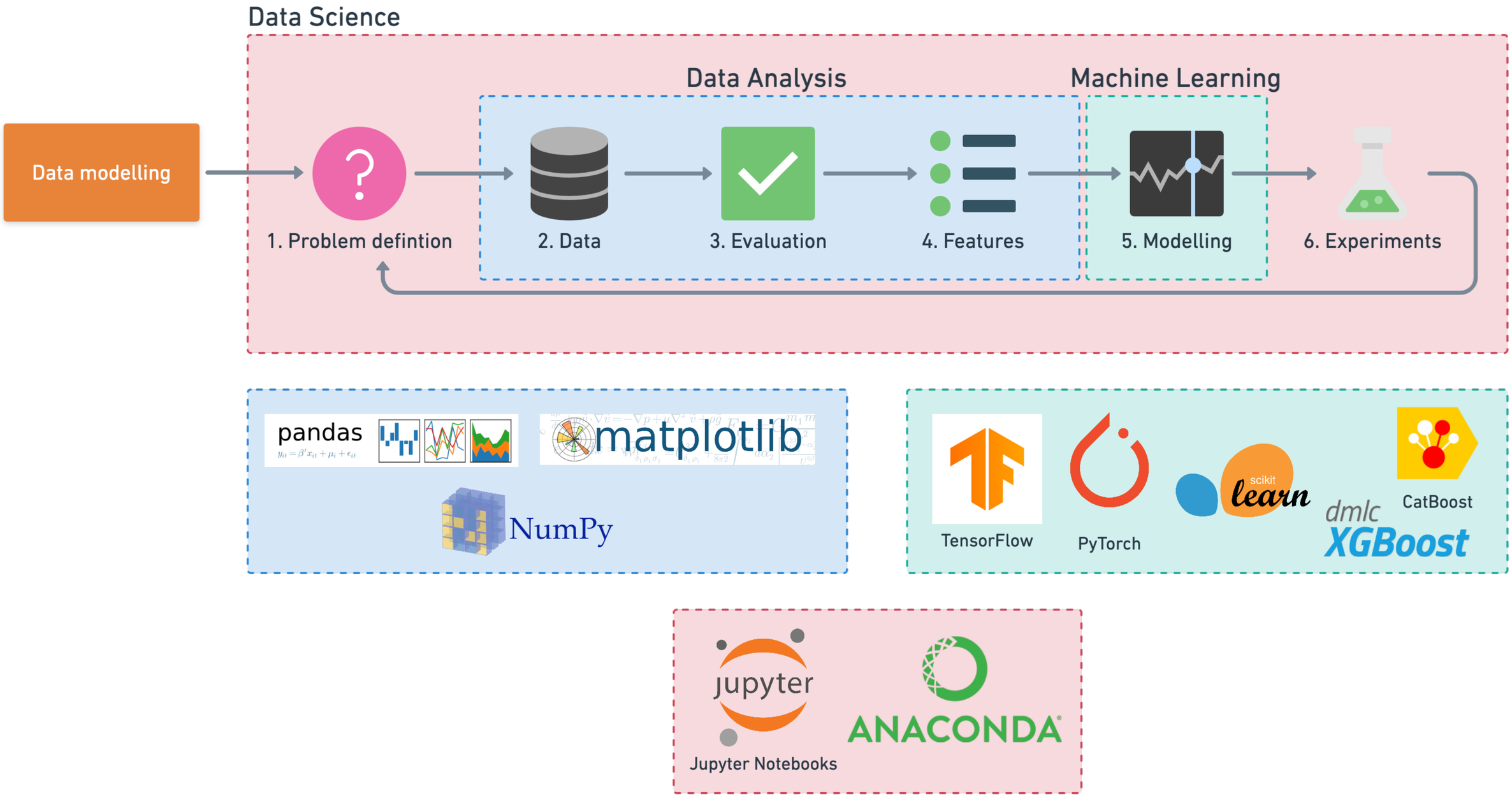


Tools you can use



This is for after creating env.

= ~3 GB

There may come a time where you want to share the contents of your Conda environment.
This could be to share a project workflow with a colleague or with someone else who's trying to set up their system to have access to the same tools as yours.
There a couple of ways to do this:
1. Share your entire project folder (including the environment folder containing all of your Conda packages).
2. Share a .yml (pronounced YAM-L) file of your Conda environment.
The benefit of 1 is it's a very simple setup, share the folder, activate the environment, run the code. However, an environment folder can be quite a large file to share.
That's where 2 comes in. A .yml is basically a text file with instructions to tell Conda how to set up an environment.
For example, to export the environment we created earlier at /Users/daniel/Desktop/project_1/env as a YAML file called environment.yml we can use the command:
conda env export --prefix /Users/daniel/Desktop/project_1/env > environment.yml
After running the export command, we can see our new .yml file stored as environment.yml.
A sample .yml file might look like the following:

```
name: my_ml_env
dependencies:
  - numpy
  - pandas
  - scikit-learn
  - jupyter
  - matplotlib
```

Of course, your actual file will depend on the packages you've installed in your environment.
For more on sharing an environment, check out the Conda documentation on sharing environments.
Finally, to create an environment called env_from_file from a .yml file called environment.yml, you can run the command:
conda env create --file environment.yml --name env_from_file
For more on creating an environment from a .yml file, check out the Conda documentation on creating an environment from a .yml file.

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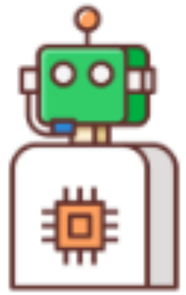
Up next



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Software Distributions

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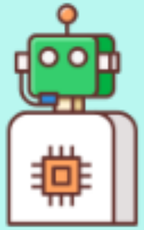


Package Manager

Your computer

MINICONDA® + CONDA®

matplotlib

NumPy

pandas

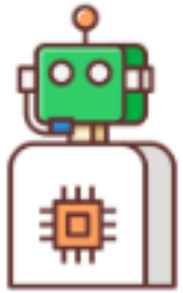
jupyter

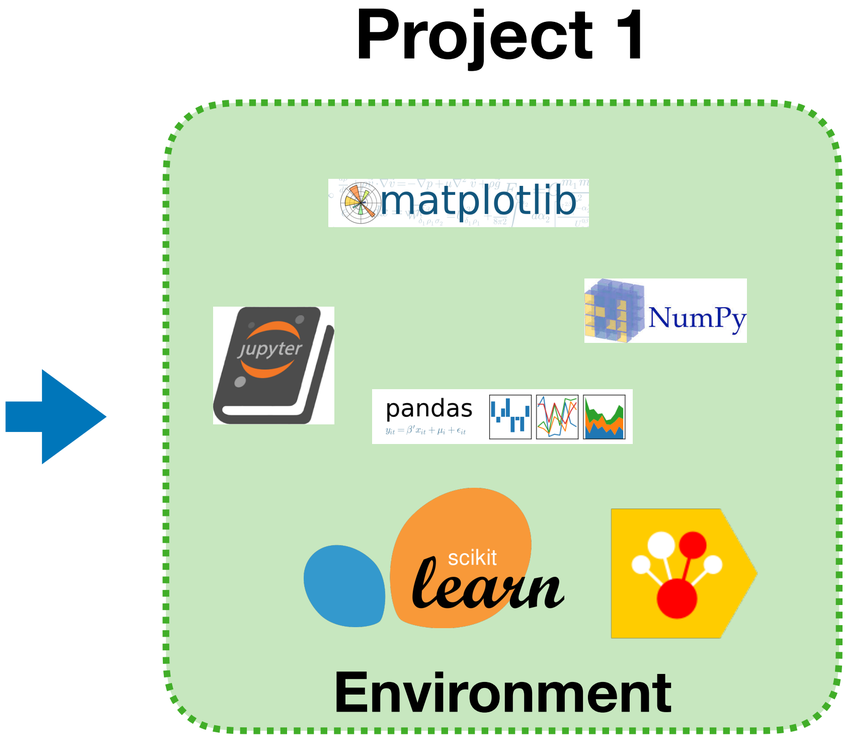
scikit learn

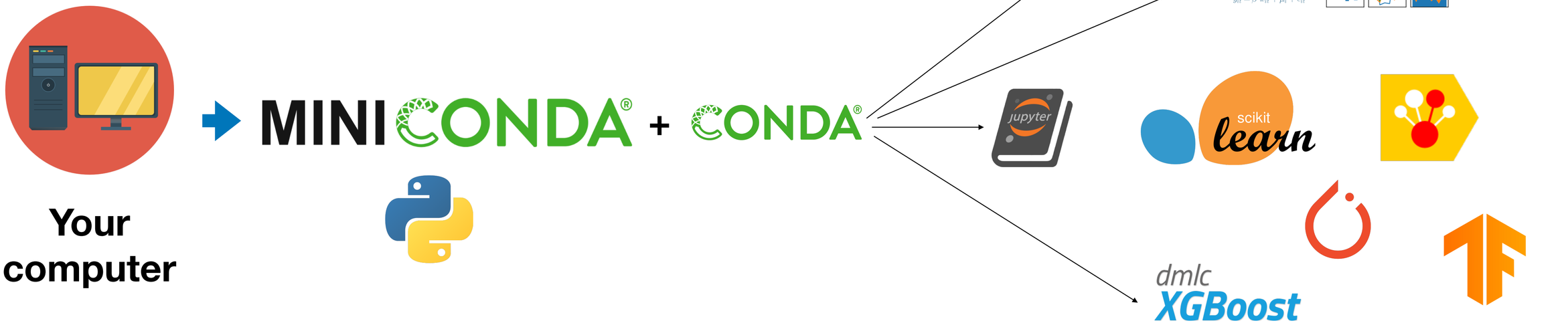
dmlc XGBoost

Up next


CONDA®




Project 1
matplotlib
NumPy
jupyter
pandas
scikit
learn
Environment



Steps to take in new project :

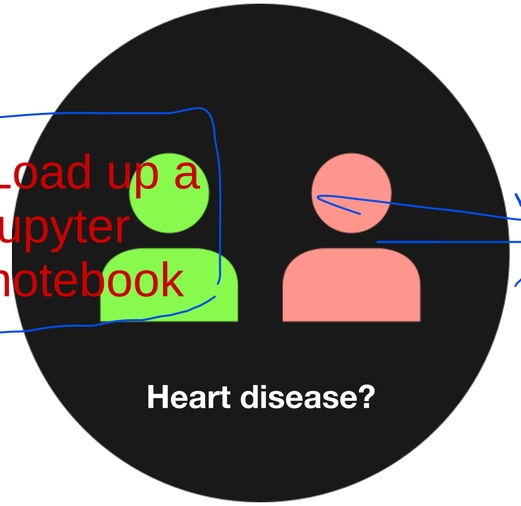
Start new project ⇒ Create new project folder ⇒ Store all relevent files (environment, data, notebooks) in the project folder.

Anaconda :

Download Anaconda and install it on your computer

Test the installation via terminal (conda list)

Load up a jupyter notebook



import pandas, Numpy, Matplotib, sklearn

Create a custom environment using conda within the project folder ↑

Your computer

Project Folder

ID	Weight	Sex	Blood Pressure	Chest pain	Heart disease?
4326	110kg	M	120/80	4	Yes
5681	64kg	F	130/90	1	NO
7911	81kg	M	130/80	0	NO

Table 1.0: Patient records

Data

CONDA

matplotlib

NumPy

jupyter

pandas

scikit learn

Environment

conda create --prefix ./env pandas numpy matplotlib scikit-learn → using this command.

All you have to do now is share the sample_project_1 folder with your team since environment is already setup and can run anywhere!

Your computer

Someone else's computer

Project Folder

ID	Weight	Sex	Blood Pressure	Chest pain	Heart disease?
4328	110Kg	M	120/80	4	yes
5681	64Kg	F	130/90	1	NO
7911	81Kg	M	130/80	0	NO

Table 1.0: Patient records

Data

Environment

Project Folder

ID	Weight	Sex	Blood Pressure	Chest pain	Heart disease?
4328	110Kg	M	120/80	4	yes
5681	64Kg	F	130/90	1	NO
7911	81Kg	M	130/80	0	NO

Table 1.0: Patient records

Data

Environment

Your computer

Project Folder

CONDA

matplotlib

NumPy

jupyter

pandas

scikit learn

ID	Weight	Sex	Blood Pressure	Chest pain	Heart disease?
4326	110kg	M	120/80	4	yes
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7911	81kg	M	130/80	0	NO

Table 1.0: Patient records

Data

Environment

Project Folder

CONDA

ID	Weight	Sex	Blood Pressure	Chest pain	Heart disease?
4326	110kg	M	120/80	4	yes
5681	64kg	F	130/90	1	NO
7911	81kg	M	130/80	0	NO

Table 1.0: Patient records

Data

jupyter

Workspace

matplotlib

NumPy

pandas

scikit learn

Environment

MINI CONDA

Download Miniconda and install it on your computer

Test the installation via terminal

Create a project folder and change into it

Create a custom environment within the project folder

Activate your new environment (conda activate)

install jupyter (conda install jupyter)

Load up a Jupyter Notebookand check the tools you need

```
conda create --prefix ./env pandas numpy matplotlib scikit-learn

#To activate this environment, use
conda activate C:\Users\yaduv\OneDrive\Desktop\sample_project\env
```

that is basically the path of env,

```
# To deactivate this environment (because of doing work on another project or bcz of some other reasons)
conda deactivate
```

we can activate again using above activate command if wo

to back again to the same project,

```
import numpy
import sklearn
import pandas
import matplotlib.pyplot
```

we can use these commands in jupyter notebook

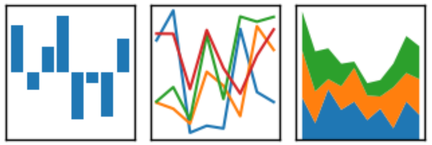
ctrl + c is for shutting down the jupyter notebook

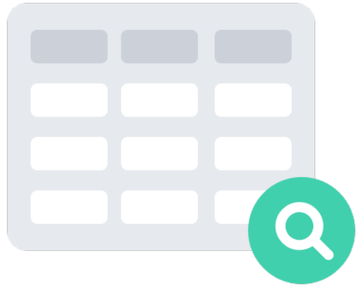
in working terminal

What is pandas?

pandas

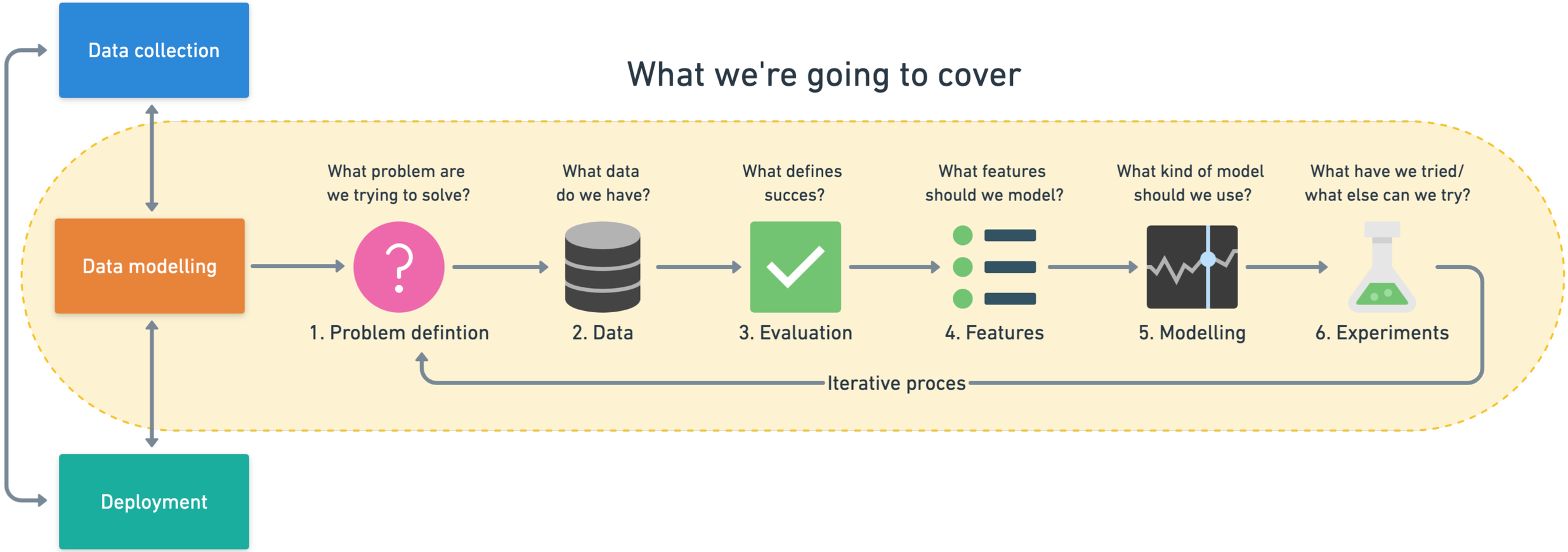
$$y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$$



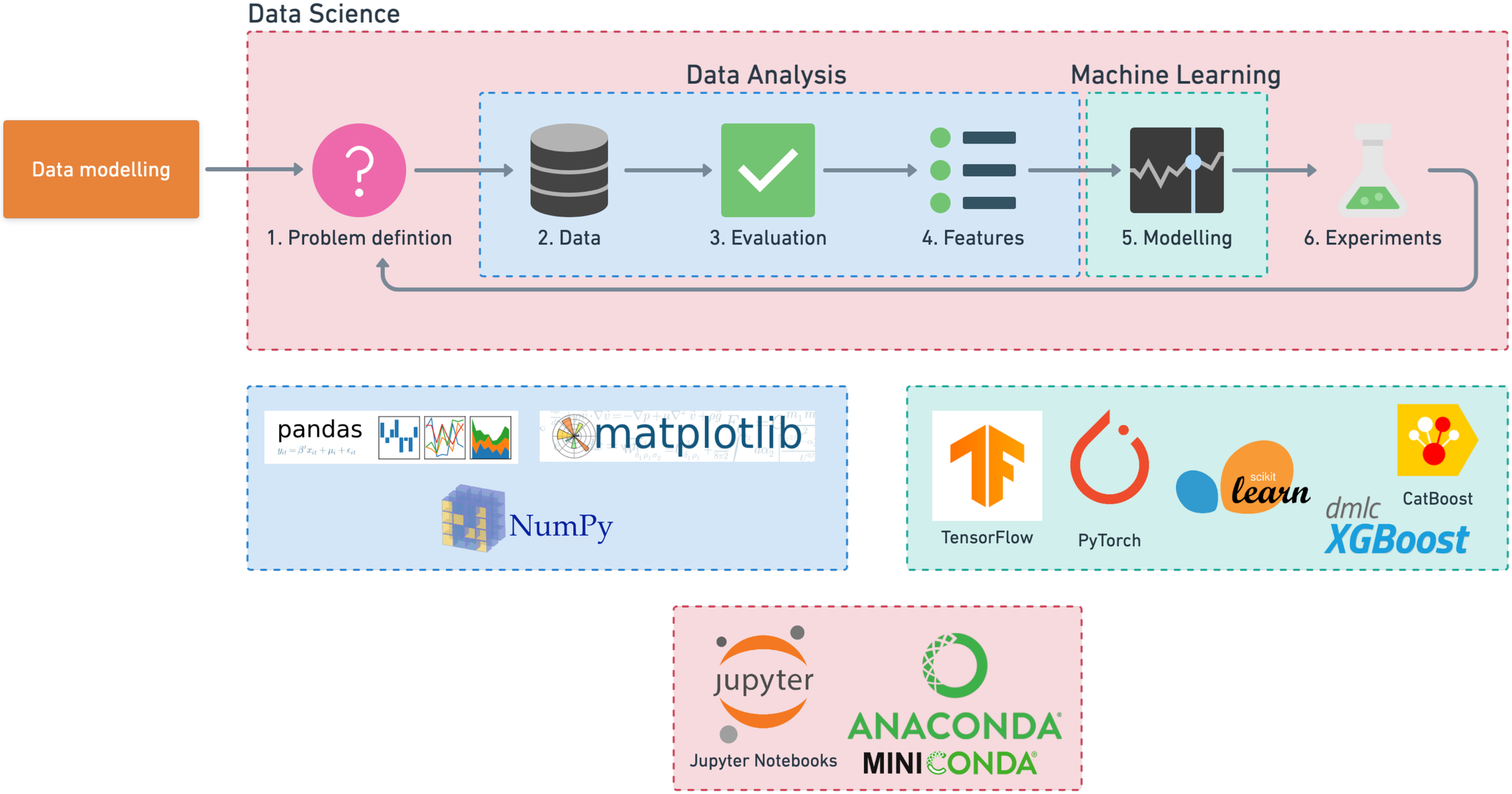


it's used to explore data, analyze data, manipulate data, get it ready for machine learning.

Steps in a full machine learning project



Tools you can use



Why pandas?

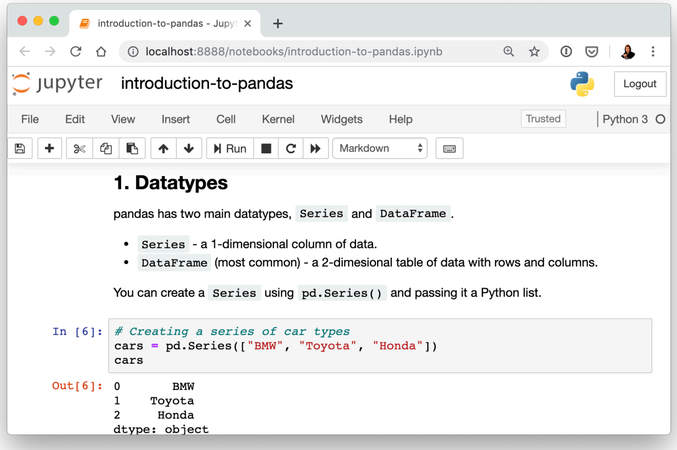
- Simple to use
- Integrated with many other data science & ML Python tools
- Helps you get your data ready for machine learning

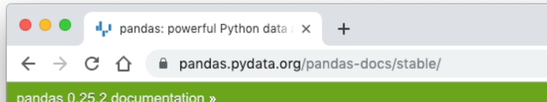
What are we going to cover?

- Most useful functions
- pandas Datatypes
- Importing & exporting data
- Describing data
- Viewing & selecting data
- Manipulating data

Where can you get help?

- Follow along with the code
- Try it for yourself
- Search for it
- Try again
- Ask

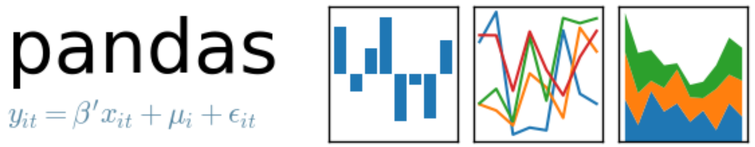




In some of the lectures, you'll notice .csv files being imported from file using something like:
heart_disease = pd.read_csv("data/heart-disease.csv")
This is helpful if you have the data downloaded to your computer or in the same directory as your notebook.
But if you don't, another great feature of pandas is being able to import .csv files directly from a URL.
For example, for the heart-disease.csv file, using the read_csv() function you can directly import it using the URL from the course GitHub repo:
heart_disease = pd.read_csv("
https://raw.githubusercontent.com/mrdbourke/zero-to-mastery-ml/master/data/heart-disease.csv")
Note: If you're using a link from GitHub, make sure it's in the "raw" format, by clicking the raw button.

Let's code!

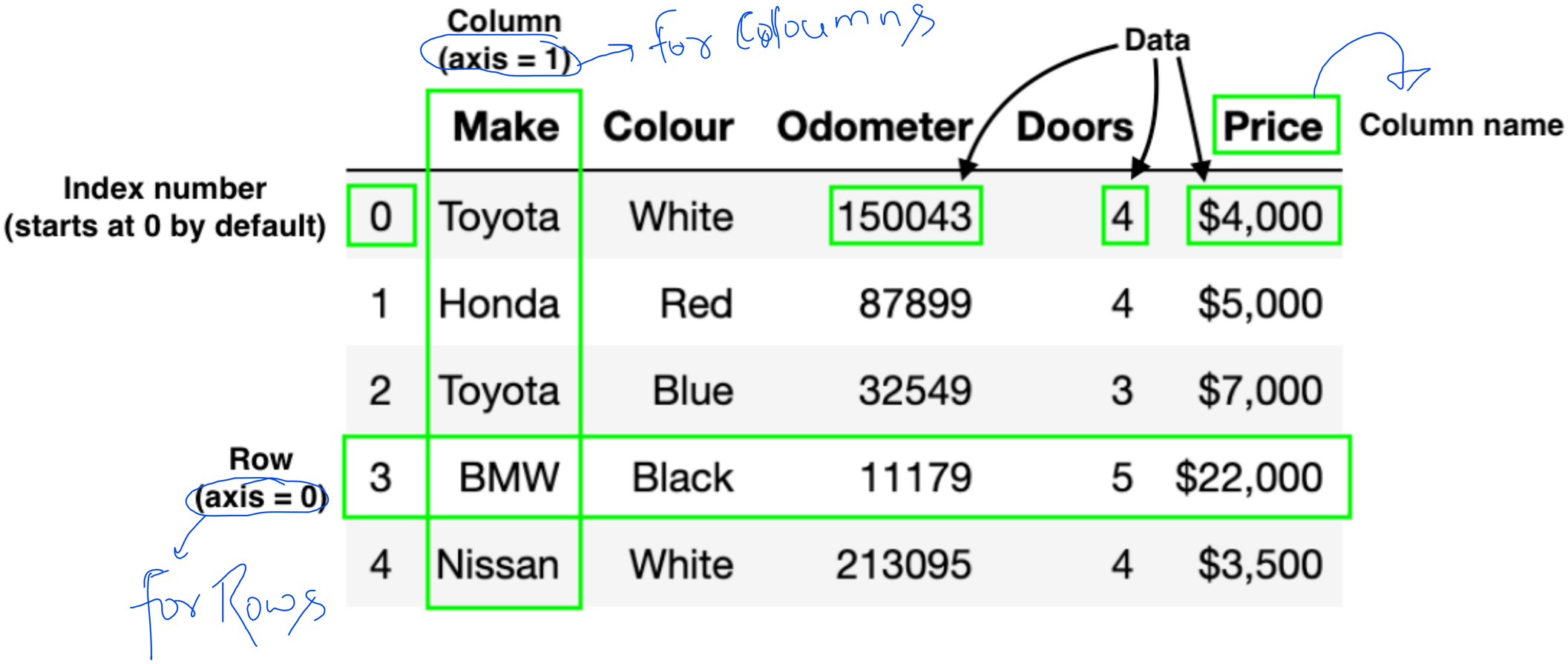
Comma-separated value (.csv)
Microsoft Excel (.xlsx)
Web page(.html)



this is a very common data storage file type and Panda's works beautifully with it.

Remember, the main difference between a function and an attribute is one doesn't have Brackett's, attributes
don't have brackets and functions, are going to perform some kind of operation.

Anatomy of a DataFrame

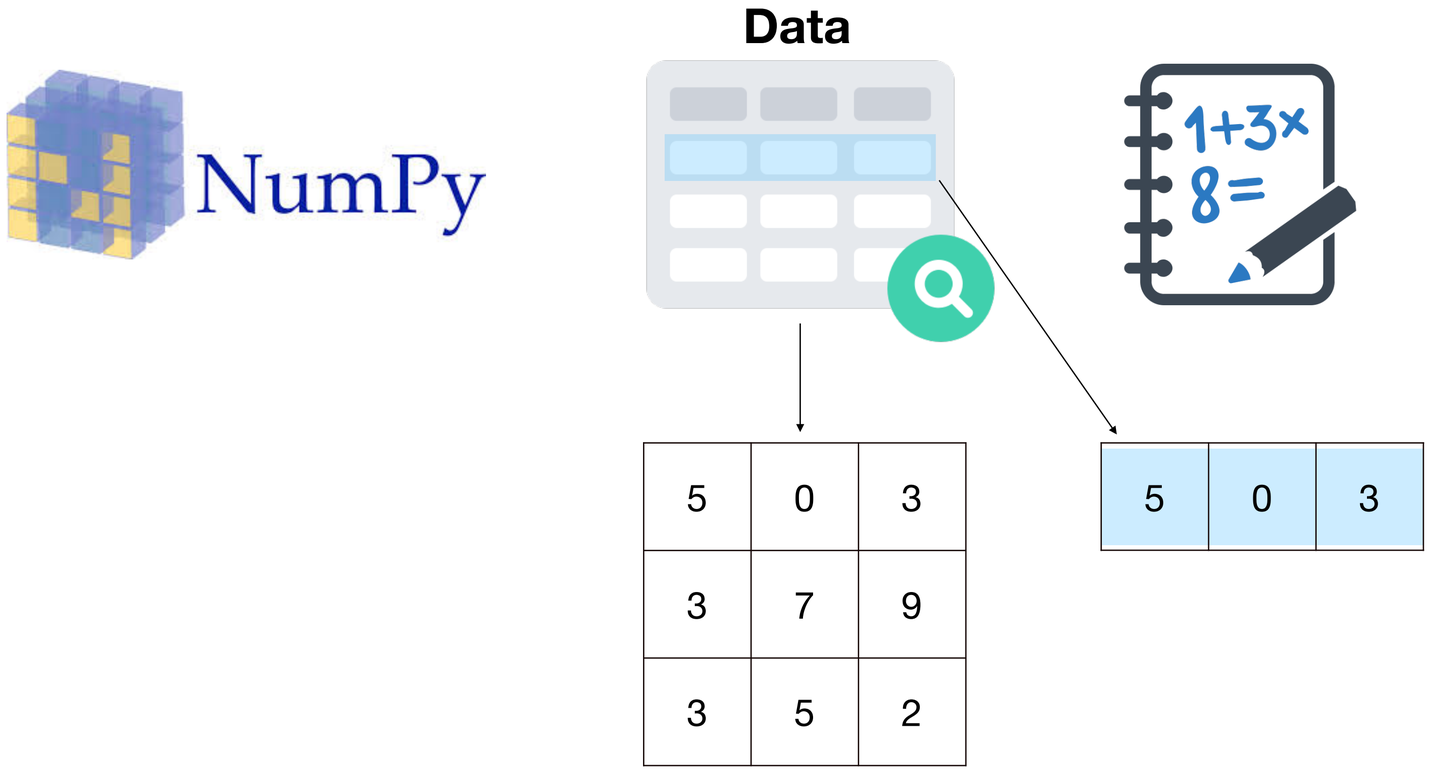


	Make	Colour	Odometer	Doors	Price
0	Toyota	White	150043	4	$4,000
1	Honda	Red	87899	4	$5,000
2	Toyota	Blue	32549	3	$7,000
3	BMW	Black	11179	5	$22,000
4	Nissan	White	213095	4	$3,500

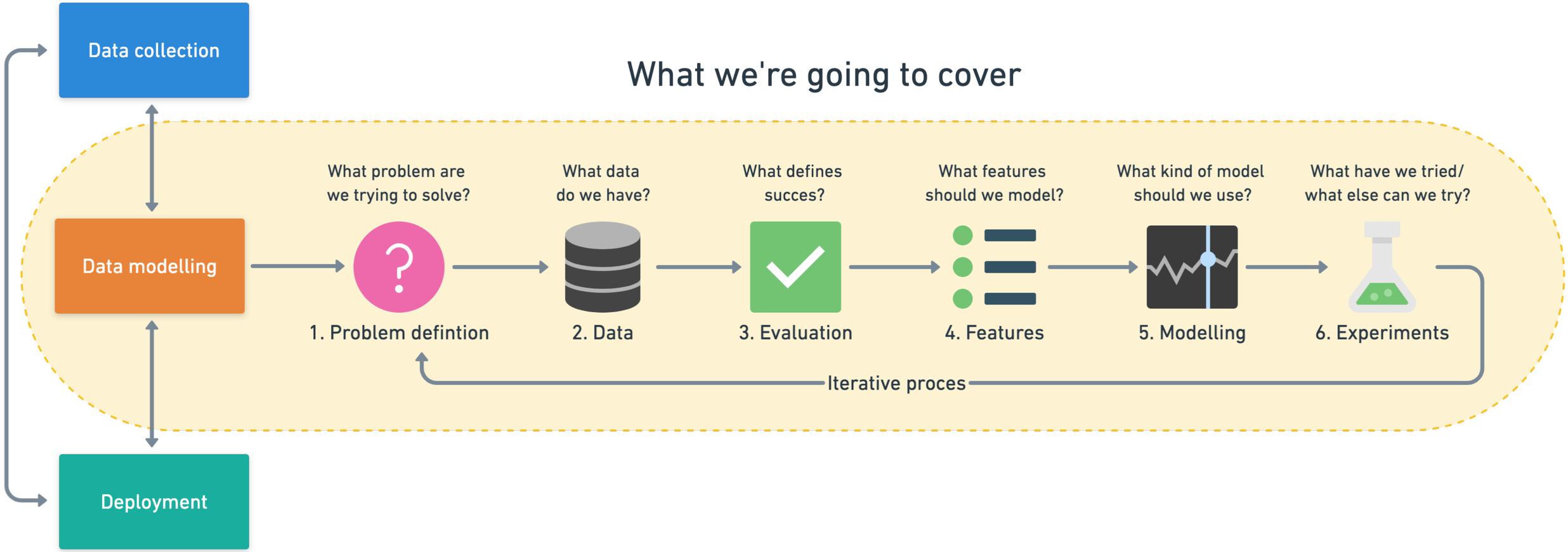
remember, in Python lists, data frames and series start from zero

many functionalities that Numpty offers us are actually written in C a programming language that is really, really fast. If we used Python lists, it would actually be a lot slower to do some of the things that we're about to do.

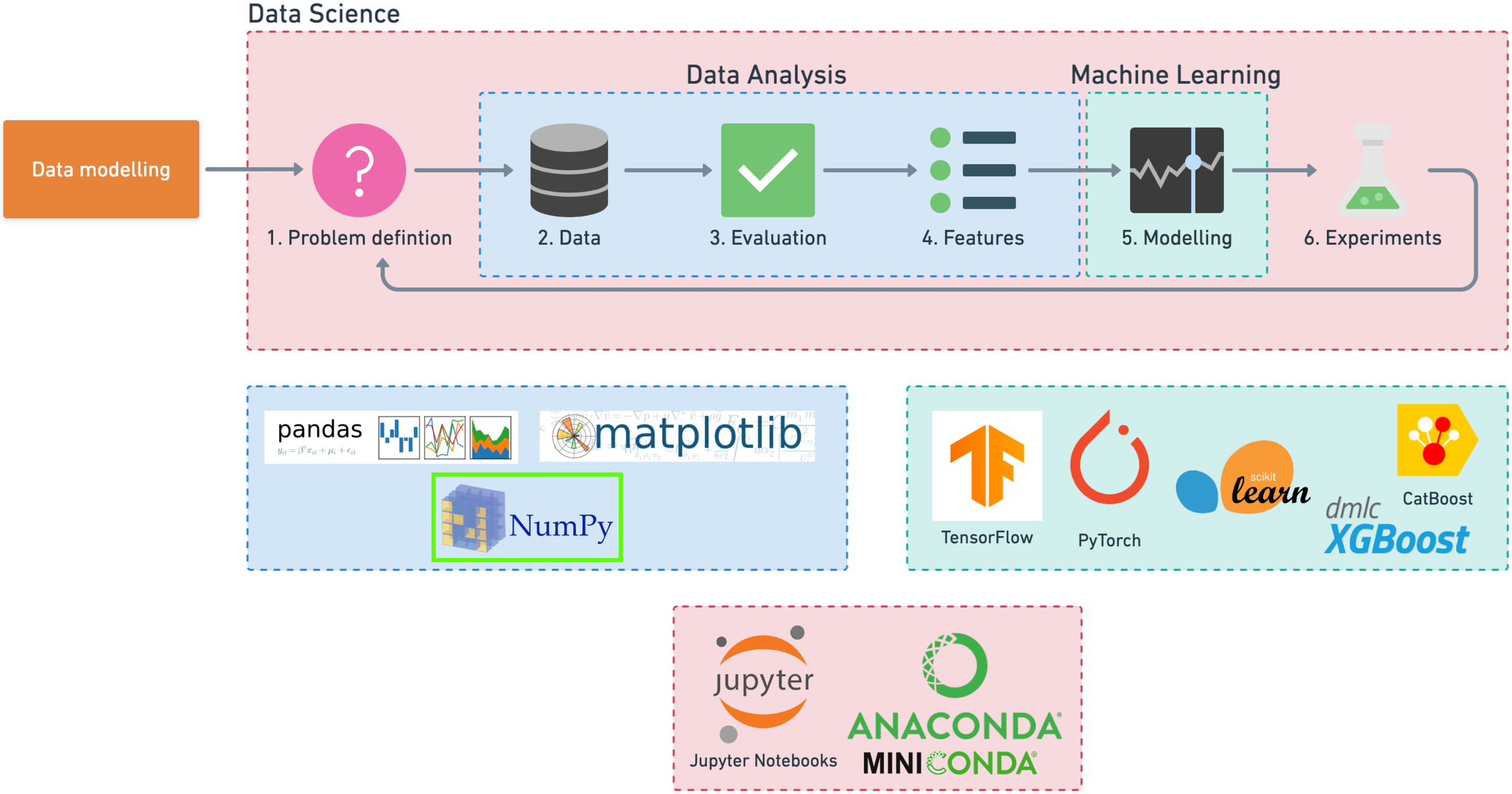
What is NumPy?



Steps in a full machine learning project



Tools you can use



Why NumPy?

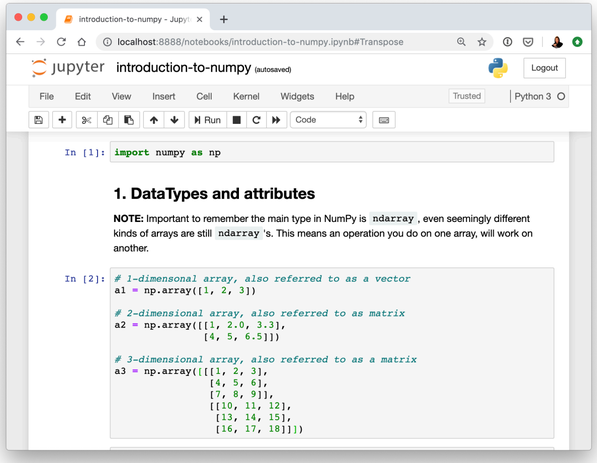
- It’s fast
- Behind the scenes optimizations written in C
- Vectorization via broadcasting (avoiding loops)
- Backbone of other Python scientific packages

What are we going to cover?

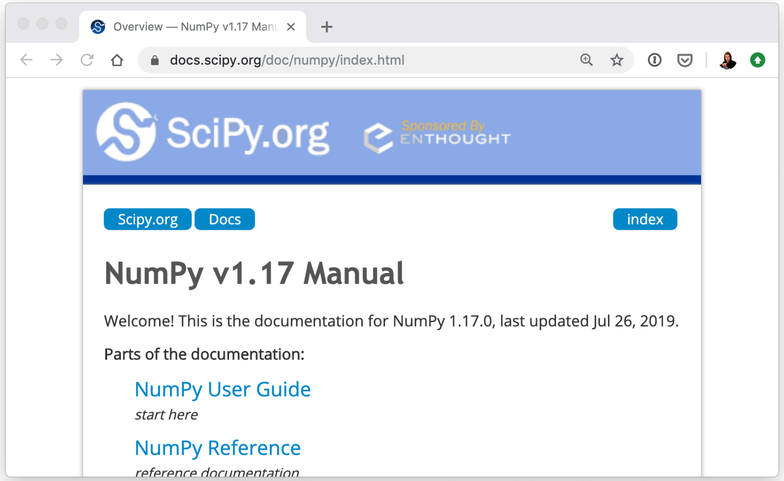
- Most useful functions
- NumPy datatypes & attributes (ndarray)
- Creating arrays
- Viewing arrays & matrices
- Manipulating & comparing arrays
- Sorting arrays
- Use cases

Where can you get help?

- Follow along with the code
- Try it for yourself
- Search for it
- Try again
- Ask



stack overflow



The main difference is the bottom left array. In the videos it's displayed incorrectly.

If you'd like to get the same array as the "Anatomy of a NumPy Array" slide shows in the following videos, run the following code:

```
# Same array as slide in video
a3 = np.array([[[1, 2, 3],
                [4, 5, 6]],
               [[7, 8, 9],
                [10, 11, 12]],
               [[13, 14, 15],
                [16, 17, 18]]])
```

Let's code!

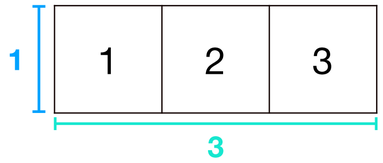
And just another reminder, figuring out the different shapes of arrays can be a bit of a challenge! It takes a fair bit of practice to get used to them.

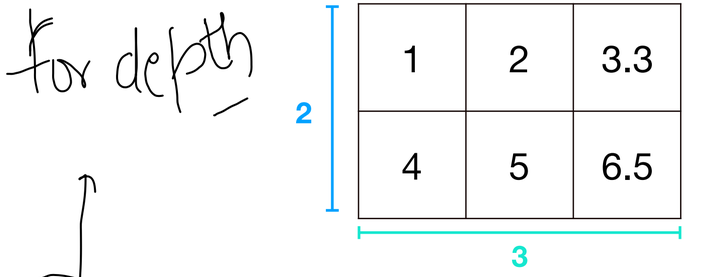
The code and concepts in the lectures are all correct, however, the slide displays the wrong array for the 3-dimensional array (you'll see these in the upcoming videos).

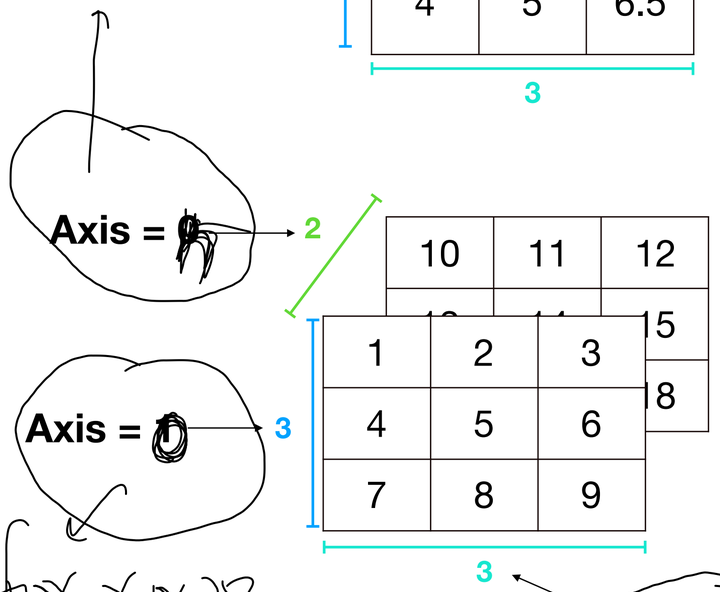
The correct slide should be:

Anatomy of a NumPy array

Data







NumPy

```
array([1, 2, 3])
```

```
array([[1. , 2. , 3.3],
       [4. , 5. , 6.5]])
```

```
array([[[ 1,  2,  3],
        [ 4,  5,  6],
        [ 7,  8,  9]],

       [[10, 11, 12],
        [13, 14, 15],
        [16, 17, 18]]])
```

Details

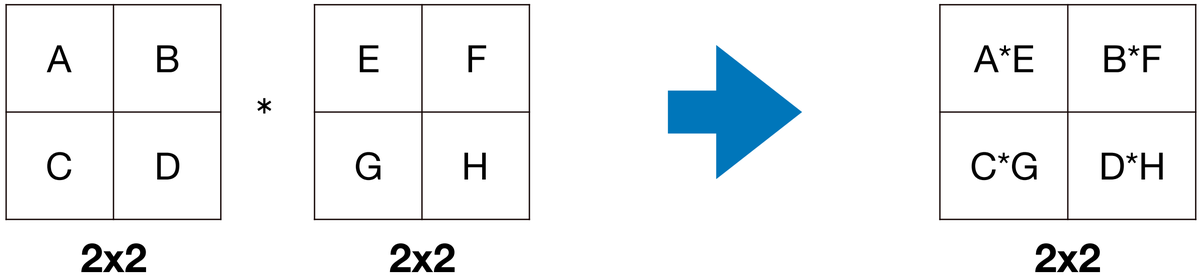
- Names: Array, vector
- 1-dimensional
- Shape = (1, 3)

- Names: Array, matrix
- More than 1-dimension
- Shape = (2, 3)

- Names: Array, matrix
- More than 1-dimension
- Shape = (2, 3, 3)

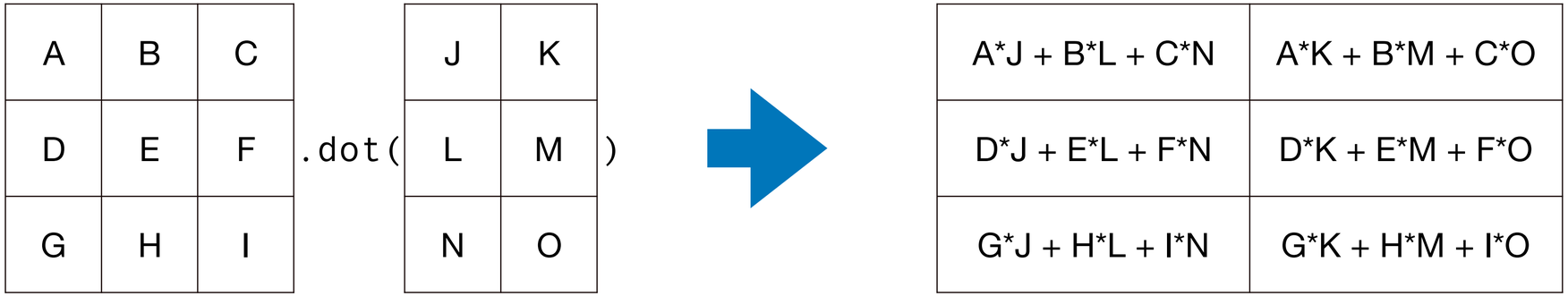
Dot product vs. element-wise

Element-wise



2x2 **2x2** **2x2**

Dot product



3x3 **3x2** **3x2**

Dot product

A	B	C
D	E	F
G	H	I

.dot(

J	K
L	M
N	O

)

A*J + B*L + C*N	A*K + B*M + C*O
D*J + E*L + F*N	D*K + E*M + F*O
G*J + H*L + I*N	G*K + H*M + I*O

3x3 ⟷ **3x2**

3x2

Numbers on the inside must match

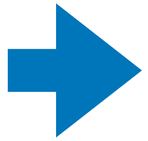
New size is same as outside numbers

5	0	3
3	7	9
3	5	2

.dot(

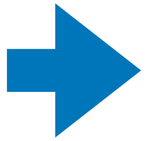
4	7
6	8
8	1

)



5	0	3
*	*	*
4	6	8
=	=	=

20 + 0 + 24 = 44



44	38
126	86
58	63

3x3

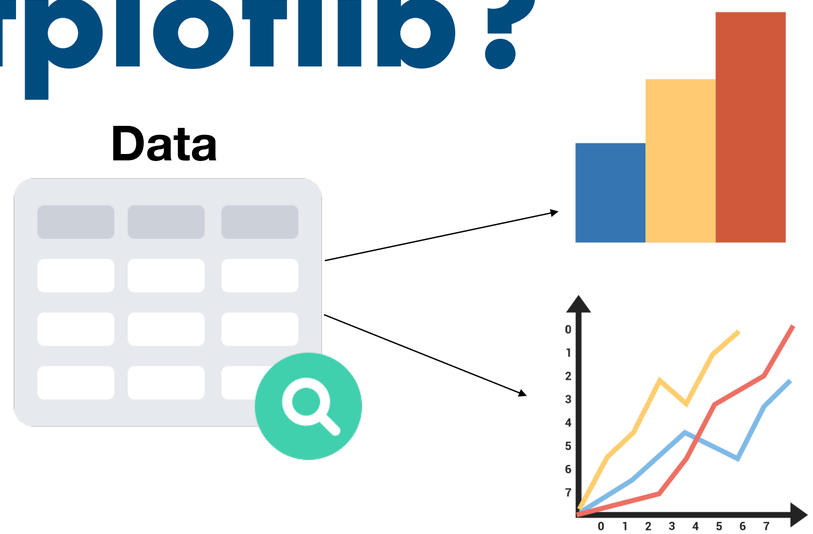
3x2

3x2

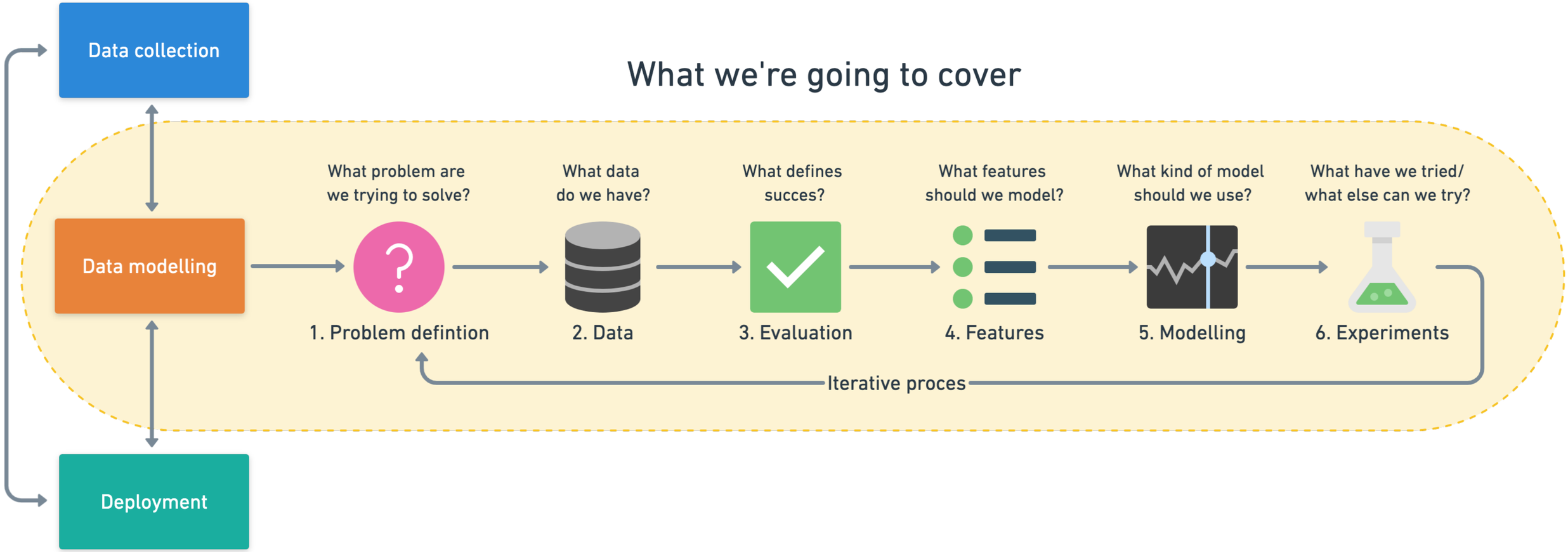
For a live demo, checkout www.matrixmultiplication.xyz

What is Matplotlib?

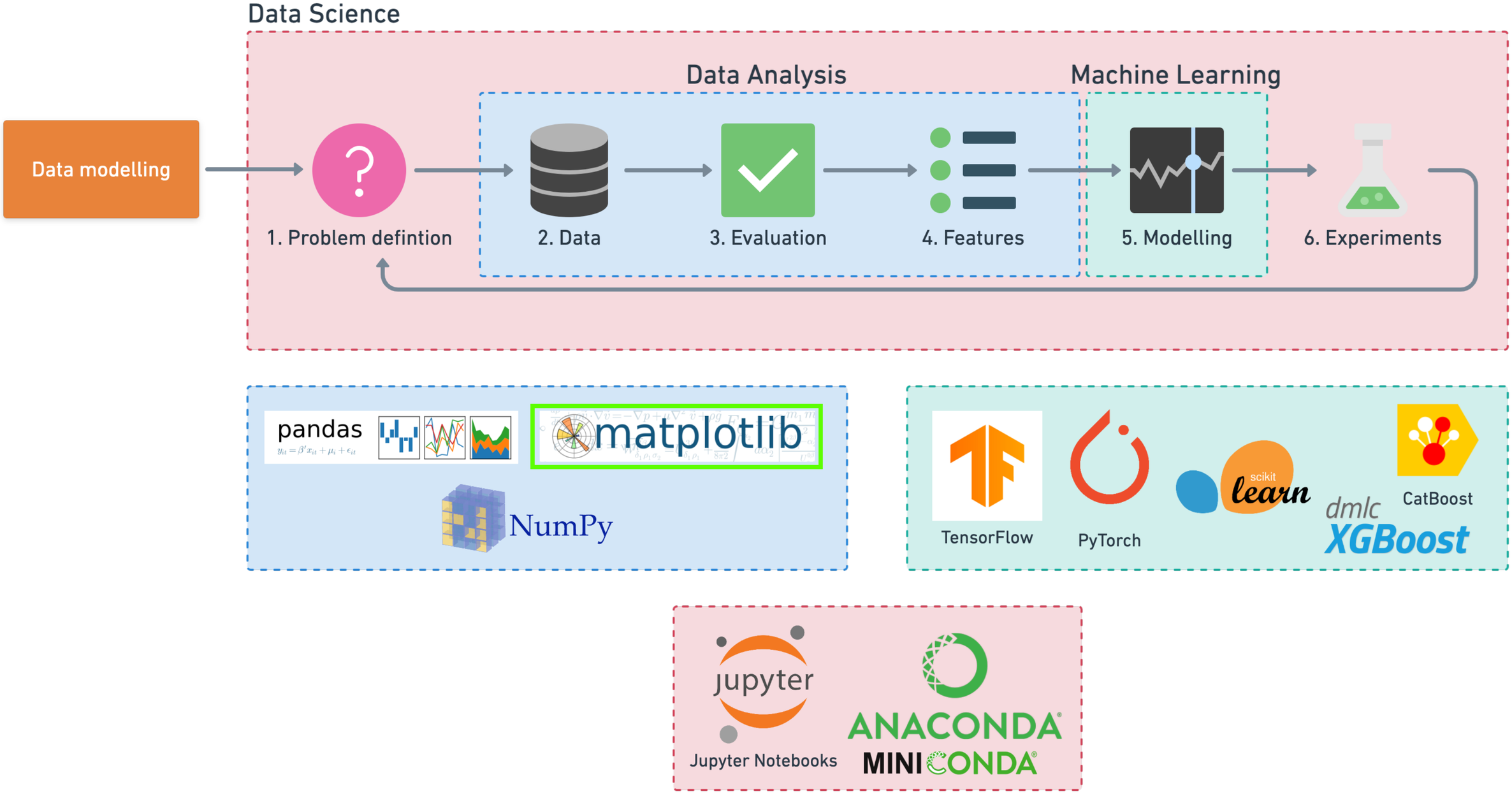
matplotlib



Steps in a full machine learning project



Tools you can use

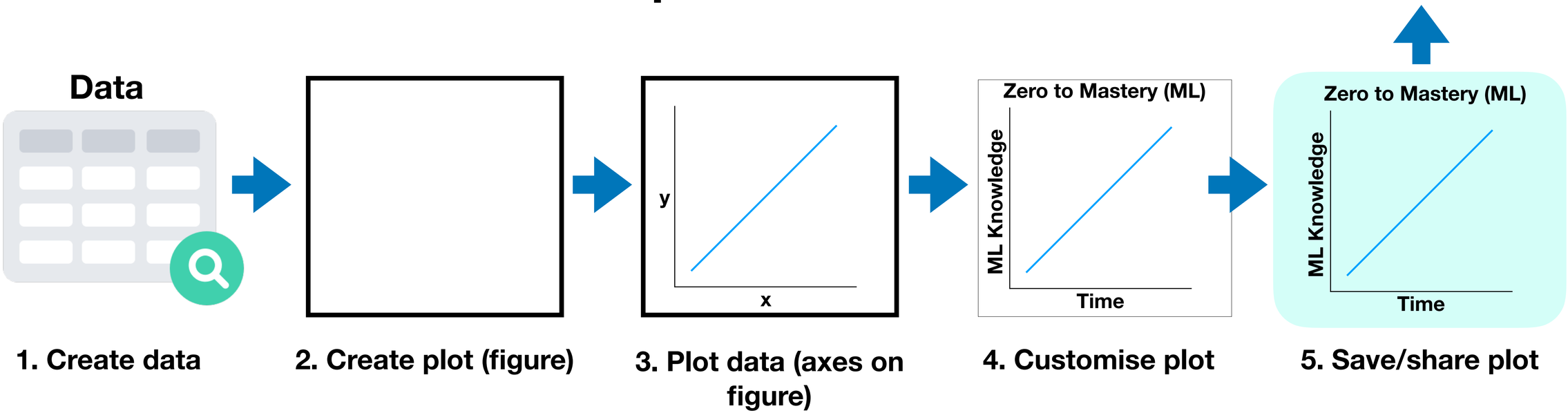


Why Matplotlib?

- Built on NumPy arrays (and Python)
- Integrates directly with pandas
- Can create basic or advanced plots
- Simple to use interface (once you get the foundations)

What are we going to cover?

A Matplotlib workflow



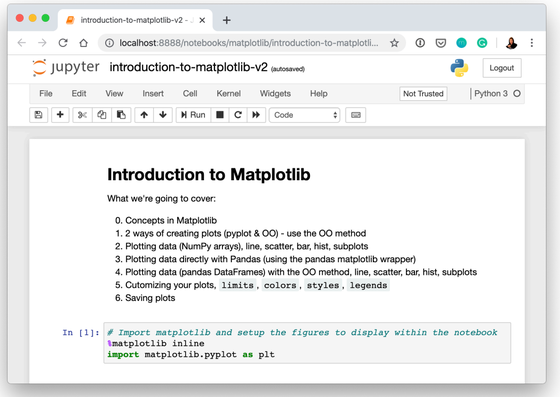
1. Create data
2. Create plot (figure)
3. Plot data (axes on figure)
4. Customise plot
5. Save/share plot

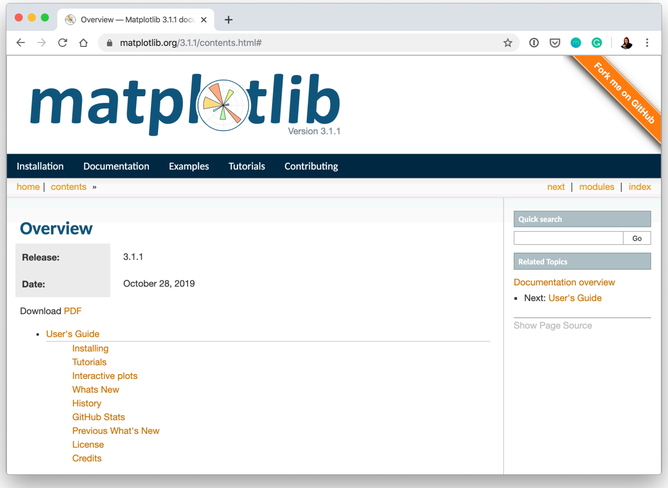
What are we going to cover?

- Matplotlib workflow
- Importing Matplotlib and the 2 ways of plotting
- Plotting data from NumPy arrays
- Plotting data from pandas DataFrames
- Customizing plots
- Saving and sharing plots

Where can you get help?

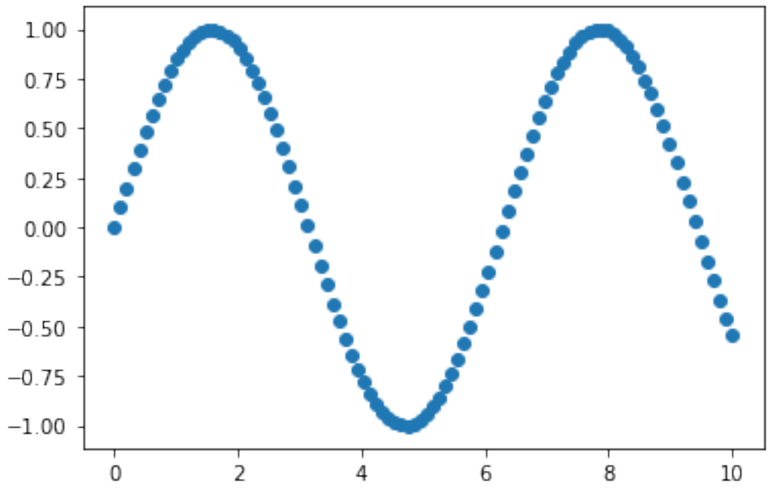
- Follow along with the code
- Try it for yourself
- Search for it
- Try again
- Ask



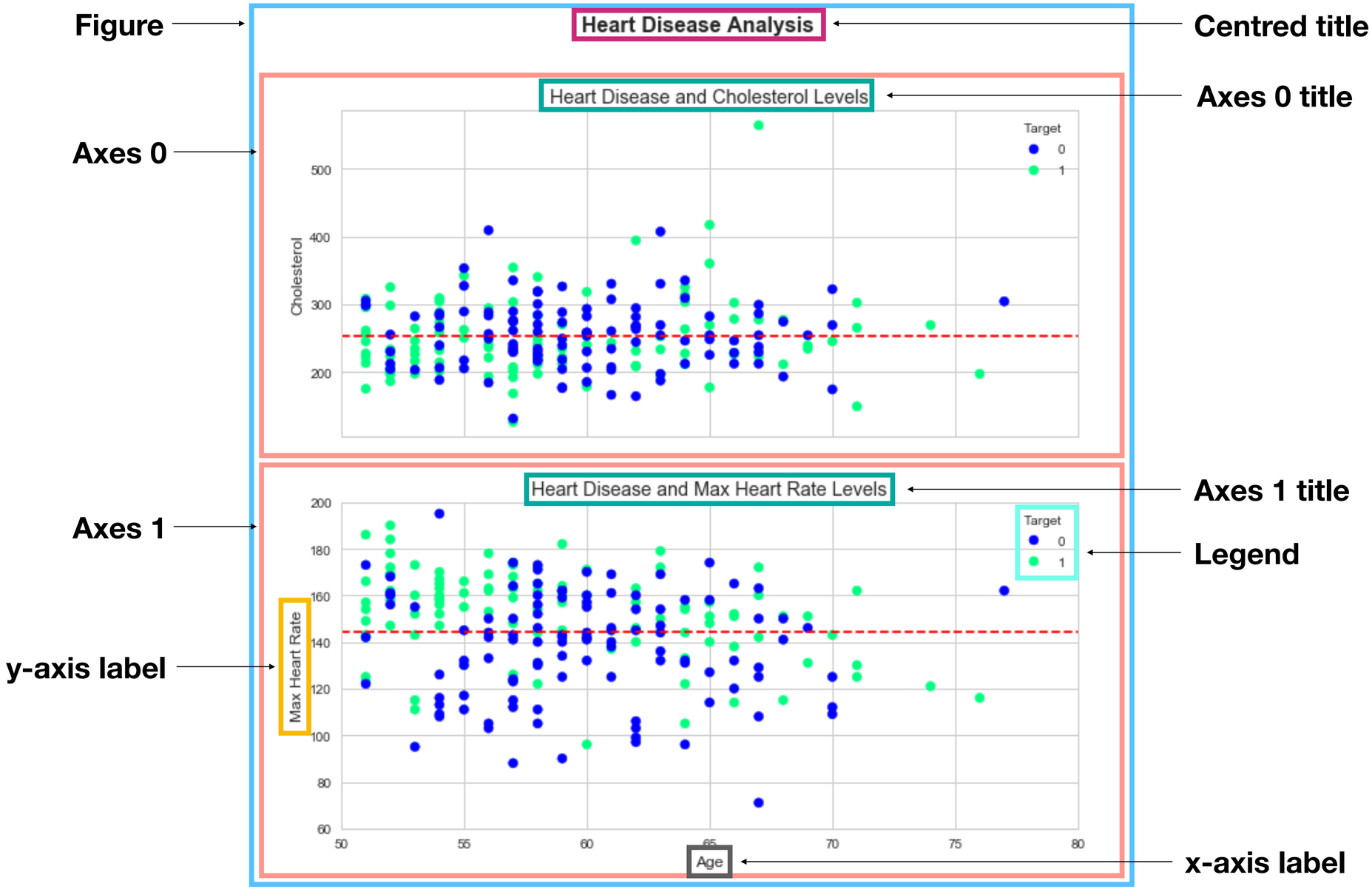


Let’s plot!

matplotlib

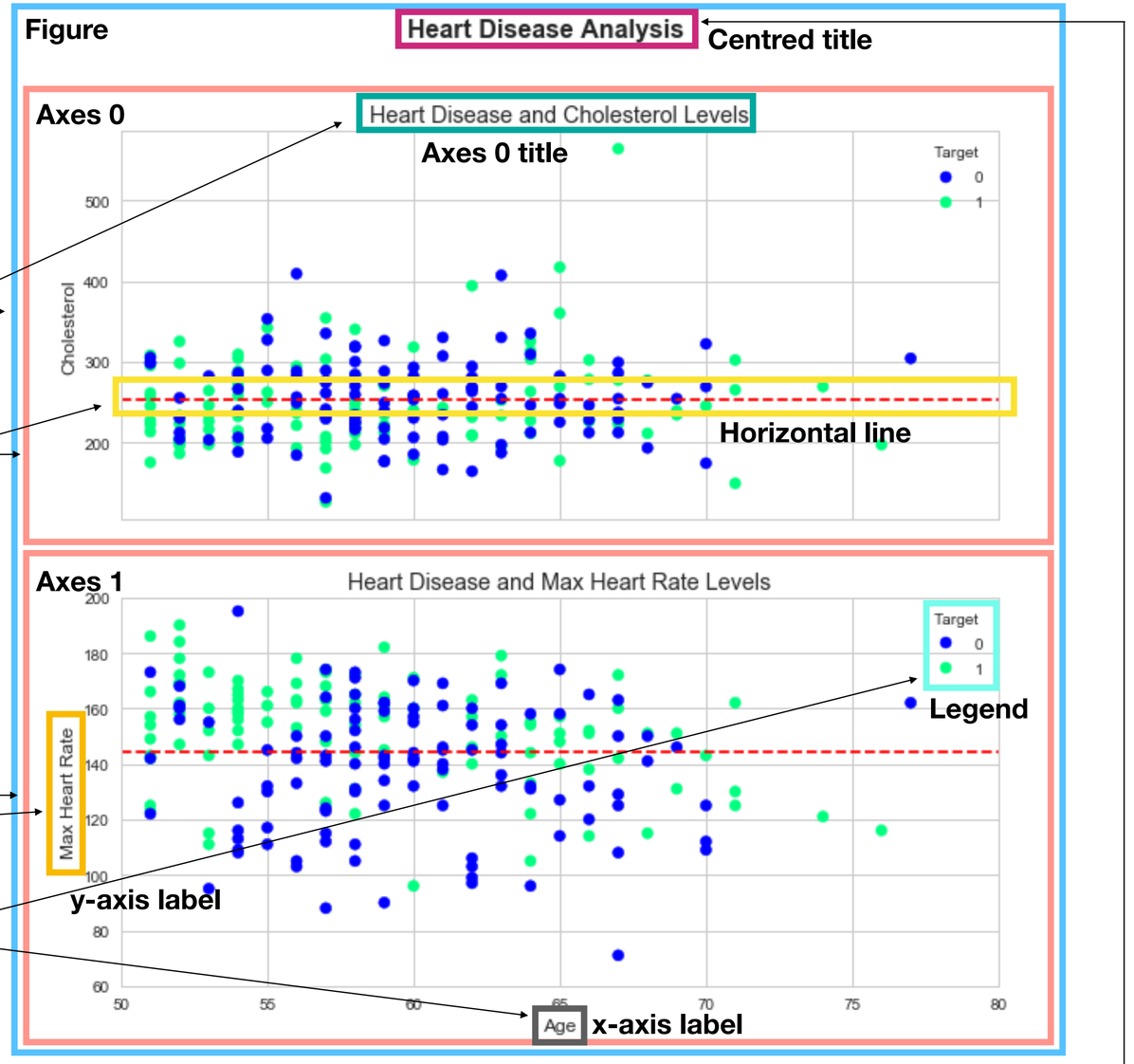


Anatomy of a Matplotlib plot

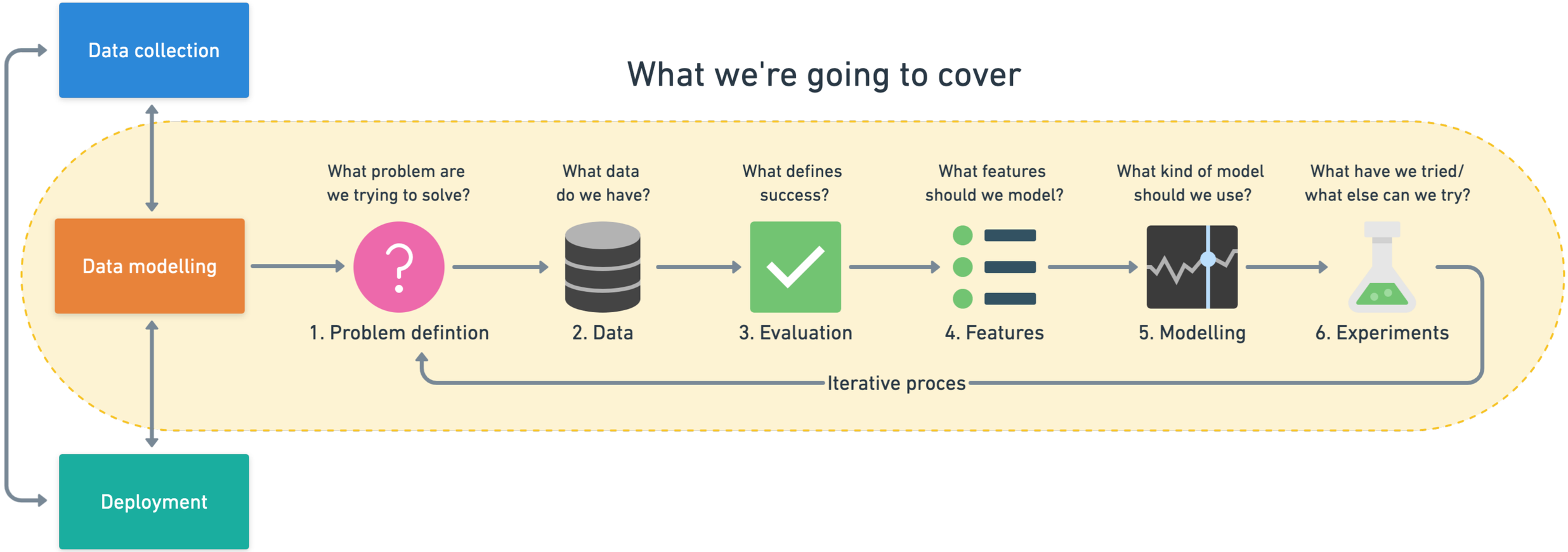


Anatomy of a Matplotlib plot

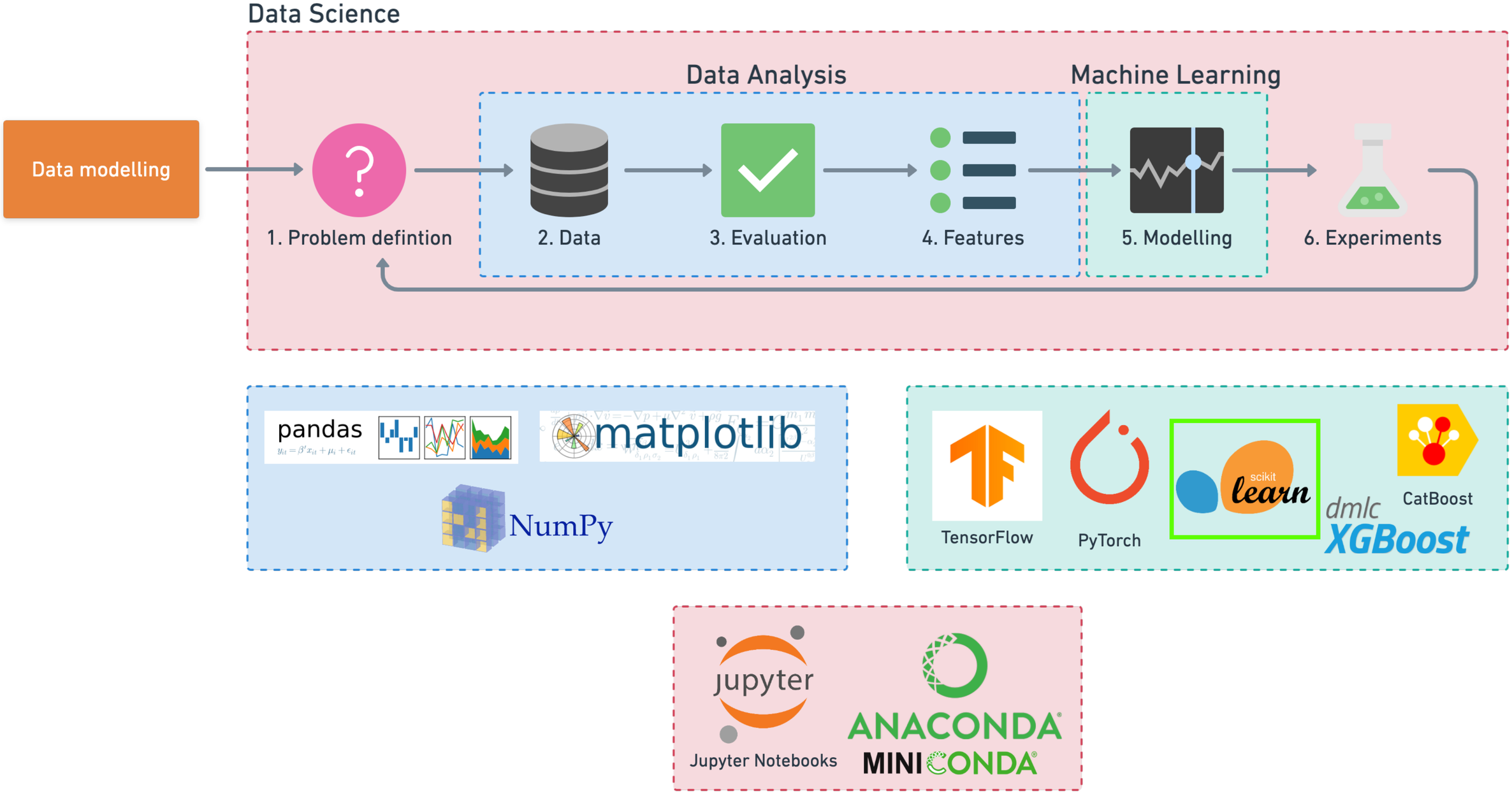
```
%matplotlib inline
import pandas as pd
import matplotlib.pyplot as plt
plt.style.use('seaborn-whitegrid') # set plot style

# Read in and manipulate data
heart_disease = pd.read_csv('../data/heart-disease.csv')
over_50 = heart_disease[heart_disease['age'] > 50]

# Create figure (plot) with 2 axes
fig, (ax0, ax1) = plt.subplots(nrows=2,
                               ncols=1,
                               sharex=True,
                               figsize=(10, 10))

# Add data, titles, meanline (axhline) and legend to axes 0
scatter = ax0.scatter(over_50["age"],
                      over_50["chol"],
                      c=over_50["target"],
                      cmap='winter')
ax0.set(title="Heart Disease and Cholesterol Levels",
        ylabel="Cholesterol",
        xlim=[50, 80])
ax0.axhline(y=over_50["chol"].mean(),
            color='r',
            linestyle='--',
            label="Average");
ax0.legend(*scatter.legend_elements(), title="Target")

# Add data, titles, meanline (axhline) and legend to axes 1
scatter = ax1.scatter(over_50["age"],
                      over_50["thalach"],
                      c=over_50["target"],
                      cmap='winter')
ax1.set(title="Heart Disease and Max Heart Rate Levels",
        xlabel="Age",
        ylabel="Max Heart Rate",
        ylim=[60, 200])
ax1.axhline(y=over_50["thalach"].mean(),
            color='r',
            linestyle='--',
            label="Average");
ax1.legend(*scatter.legend_elements(), title="Target")

# Title the figure
fig.suptitle('Heart Disease Analysis', fontsize=16, fontweight='bold');
```



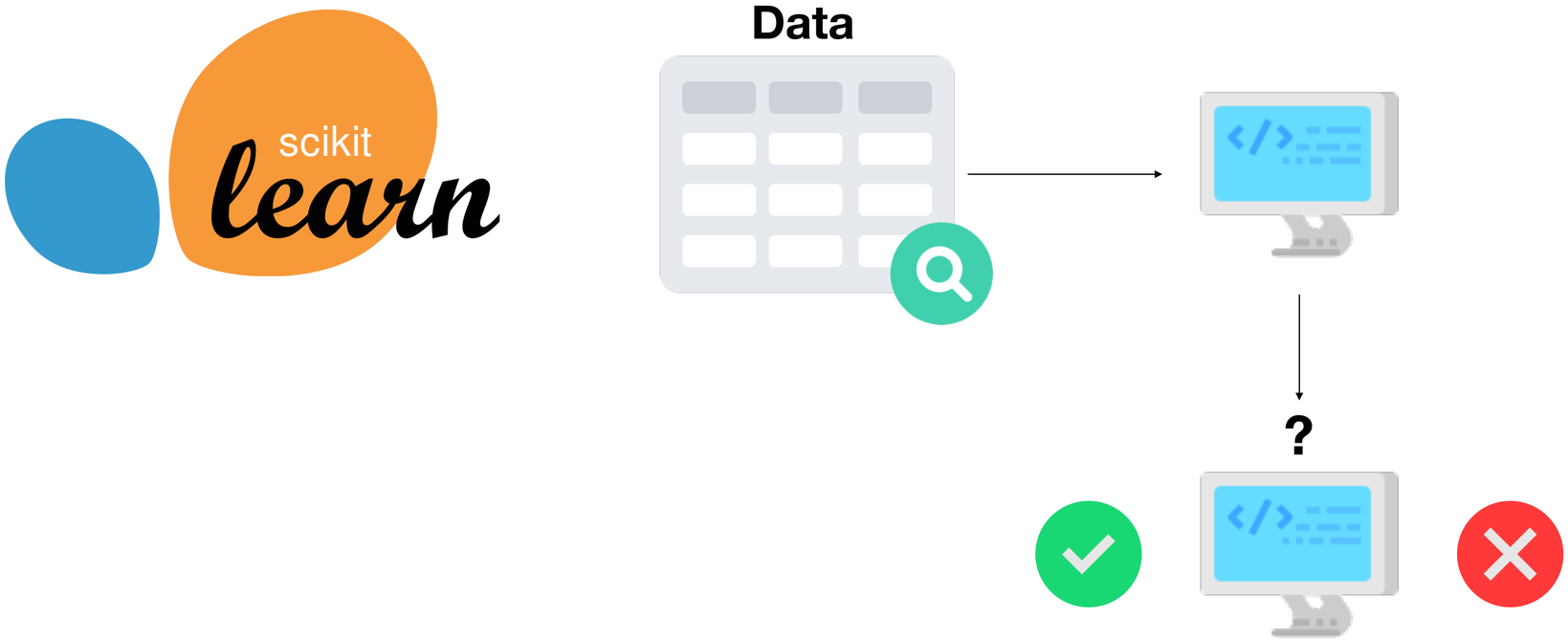
Steps in a full machine learning project



Tools you can use



What is Scikit-Learn (sklearn)?

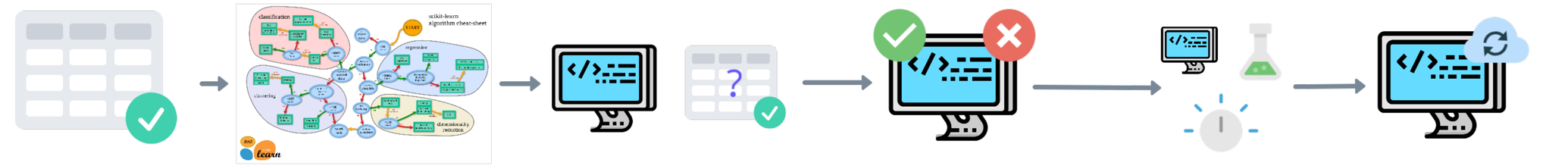


Why Scikit-Learn?

- Built on NumPy and Matplotlib (and Python)
- Has many in-built machine learning models
- Methods to evaluate your machine learning models
- Very well-designed API

What are we going to cover?

A Scikit-Learn workflow



1. Get data ready
2. Pick a model (to suit your problem)
3. Fit the model to the data and make a prediction
4. Evaluate the model
5. Improve through experimentation
6. Save and reload your trained model

What are we going to cover?

- An end-to-end Scikit-Learn workflow
- Getting data ready (to be used with machine learning models)
- Choosing a machine learning model
- Fitting a model to the data (learning patterns)
- Making predictions with a model (using patterns)
- Evaluating model predictions
- Improving model predictions
- Saving and loading models

Where can you get help?

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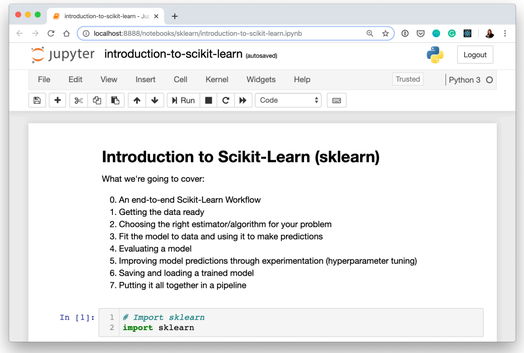
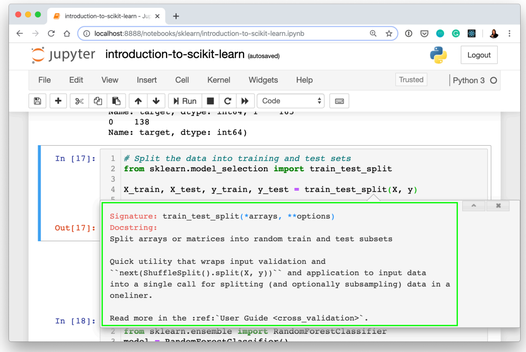
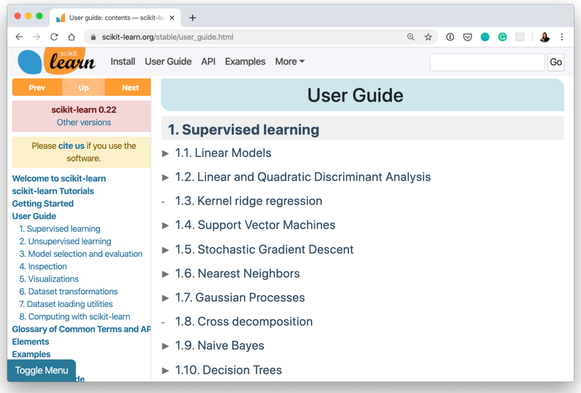




stackoverflow



Let's model!

Supervised learning

Classification

- “Is this example one thing or another?”
- Binary classification = two options
- Multi-class classification = more than two options

Regression

- “How much will this house sell for?”
- “How many people will buy this app?”

One Hot Encoding

A process used to turn categories into numbers.

Car	Colour
0	Red
1	Green
2	Blue
3	Red

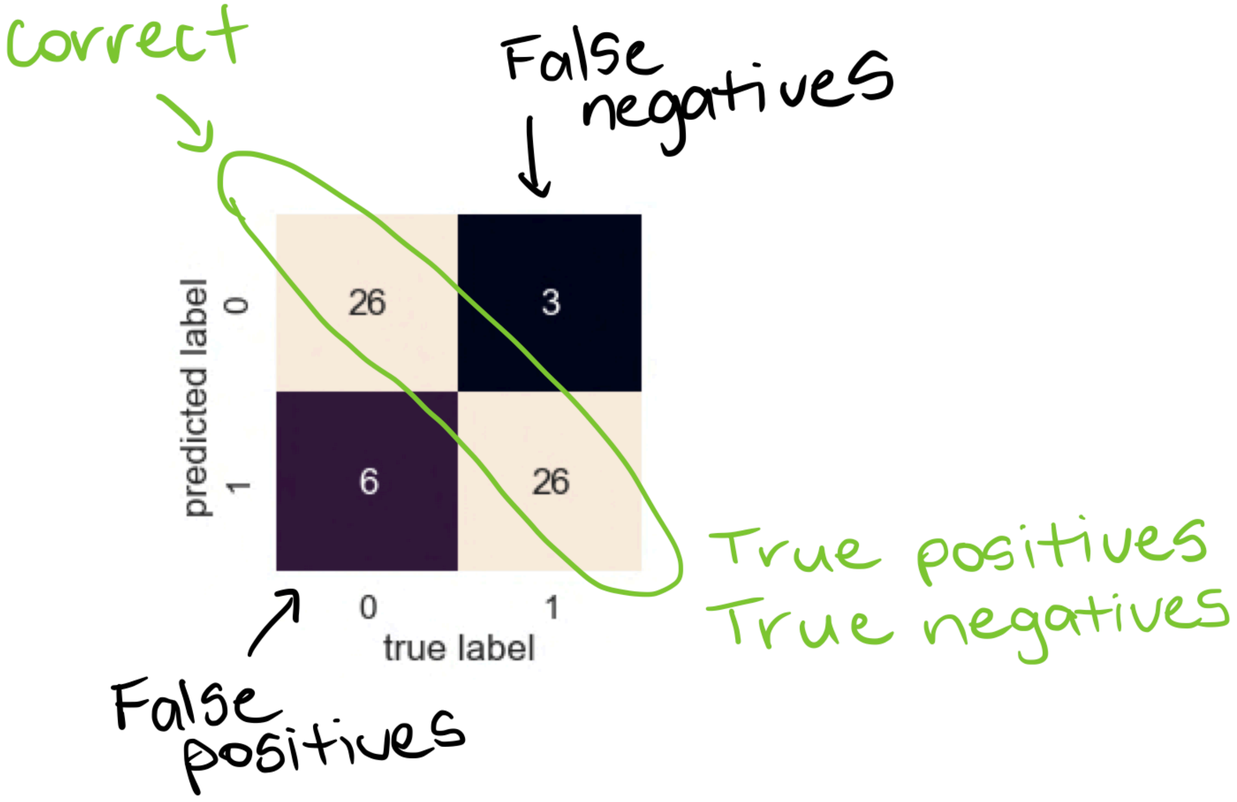
Car	Red	Green	Blue
0	1	0	0
1	0	1	0
2	0	0	1
3	1	0	0

Classification and Regression metrics

Classification	Regression
Accuracy	**R^2 (r-squared)**
Precision	Mean absolute error (MAE)
Recall	Mean squared error (MSE)
F1	Root mean squared error (RMSE)

Bold = default evaluation in Scikit-Learn

Confusion matrix anatomy



- **True positive = model predicts 1 when truth is 1**
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```python
from sklearn.metrics import classification_report

print(classification_report(y_test, y_preds))
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              precision    recall  f1-score   support

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Which regression metric should you use?

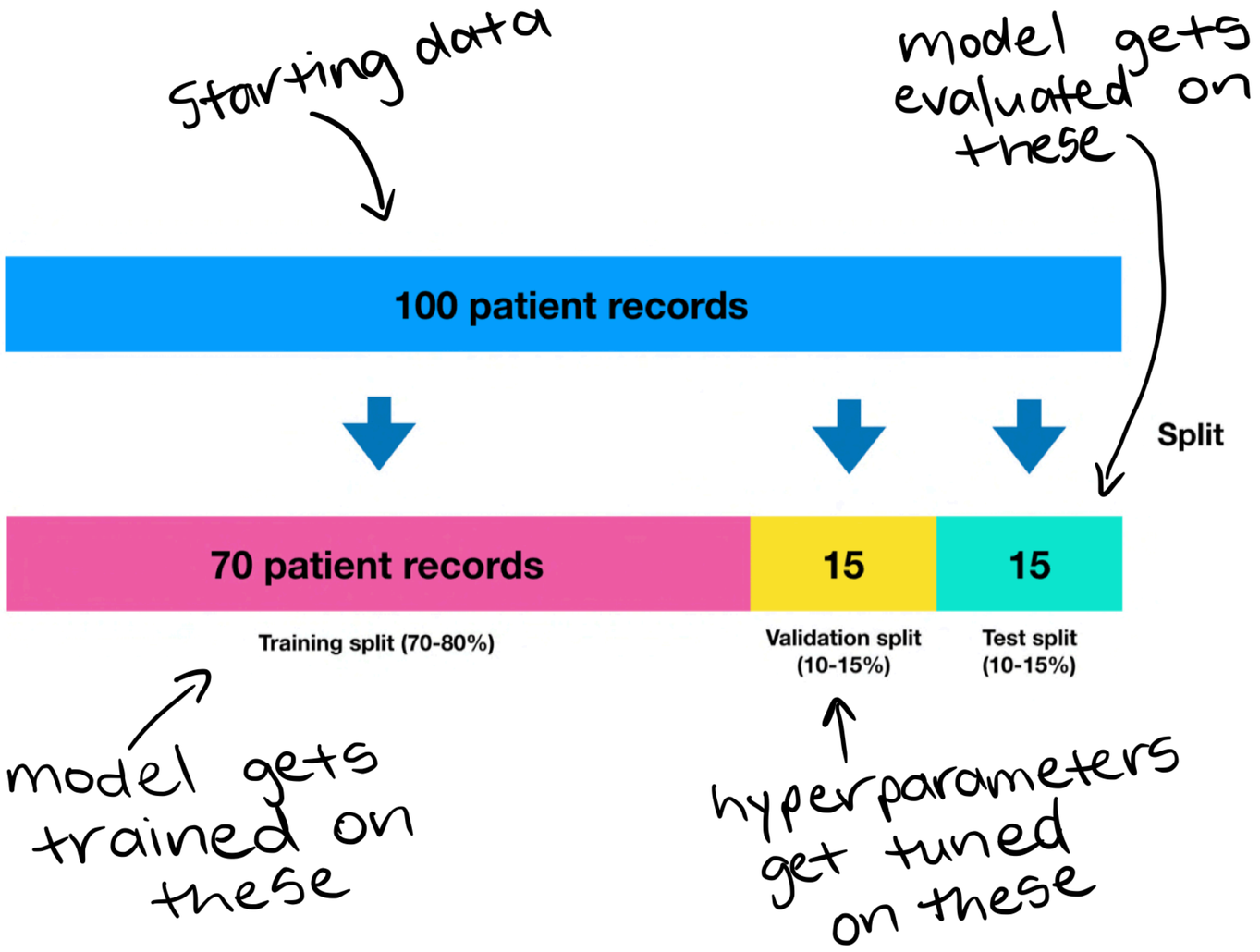
- **R^2** is similar to accuracy. It gives you a quick indication of how well your model might be doing. Generally, the closer your **R^2** value is to 1.0, the better the model. But it doesn't really tell exactly how wrong your model is in terms of how far off each prediction is.
- **MAE** gives a better indication of how far off each of your model's predictions are on average.
- As for **MAE** or **MSE**, because of the way MSE is calculated, squaring the differences between predicted values and actual values, it amplifies larger differences. Let's say we're predicting the value of houses (which we are).
  - Pay more attention to MAE: When being $10,000 off is ***twice*** as bad as being $5,000 off.
  - Pay more attention to MSE: When being $10,000 off is ***more than twice*** as bad as being $5,000 off.

Improving a model (via hyperparameter tuning)

Cooking time: 1 hour
Temperature: 180ºC

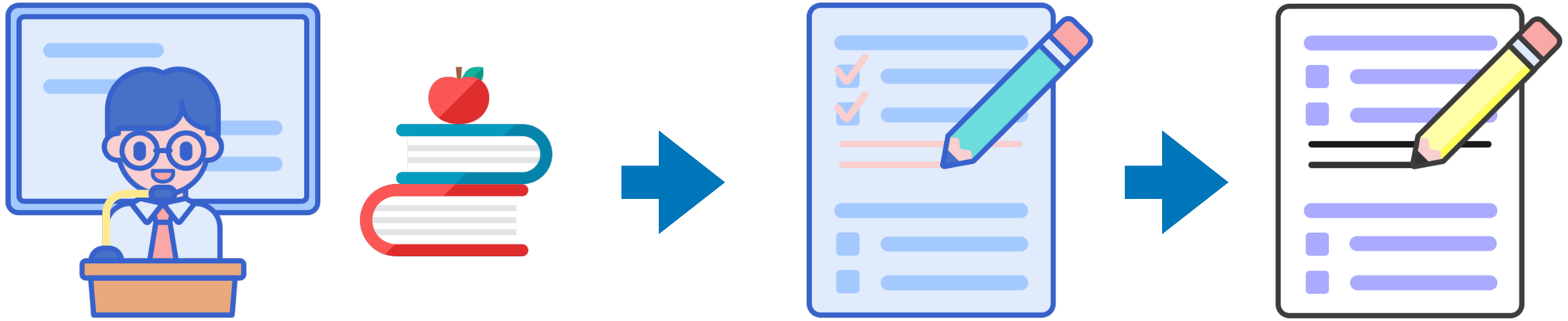
Cooking time: 1 hour
Temperature: 200ºC

Tuning Hyperparameters by Hand



The most important concept in machine learning

(the 3 sets)



Course materials (training set)

Practice exam (validation set)

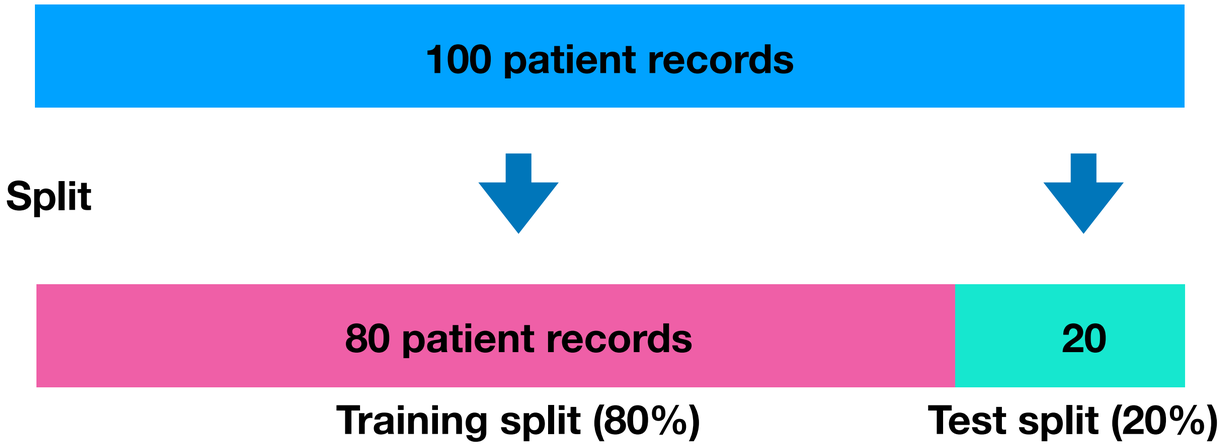
Final exam (test set)

Generalization

The ability for a machine learning model to perform well on data it hasn't seen before.

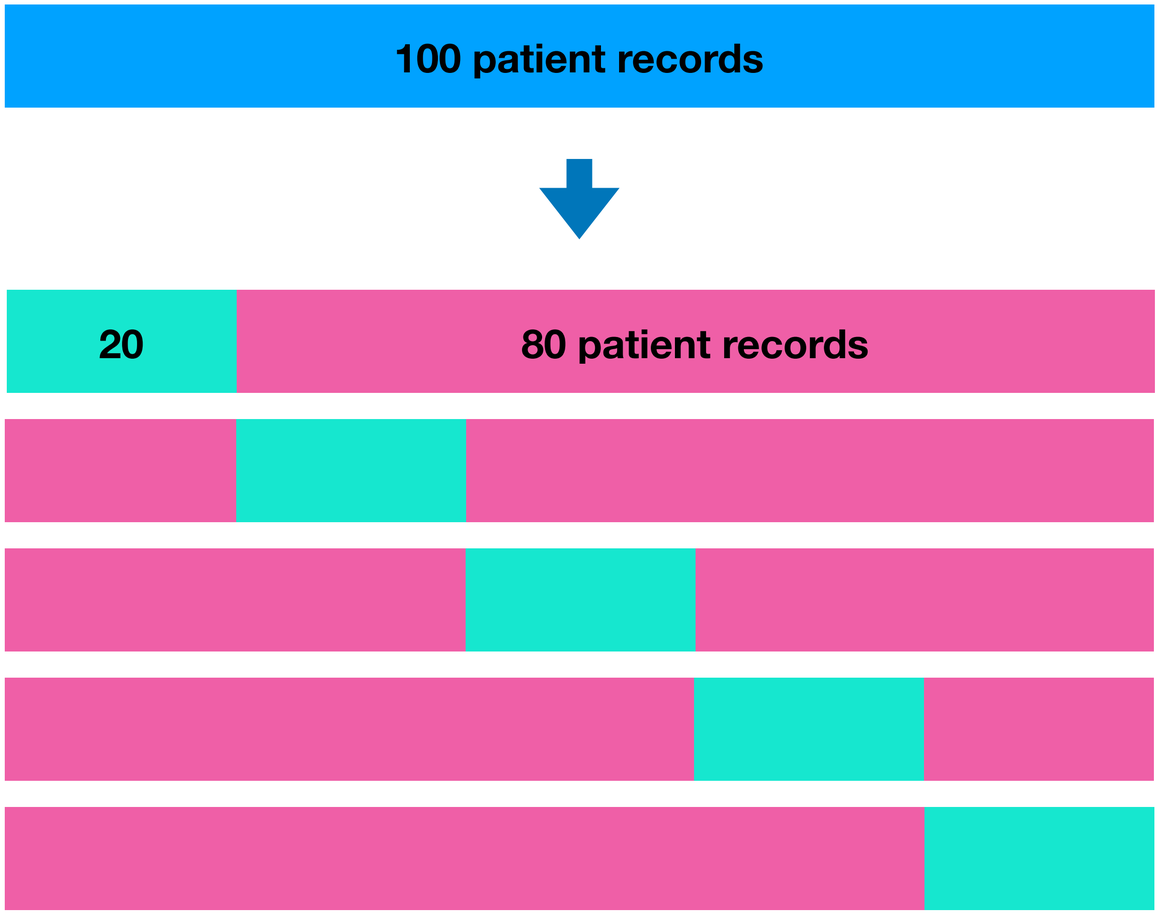
Cross-validation

Normal Train & Test Split



Model is trained on training data, and evaluated on the test data.

5-fold Cross-validation



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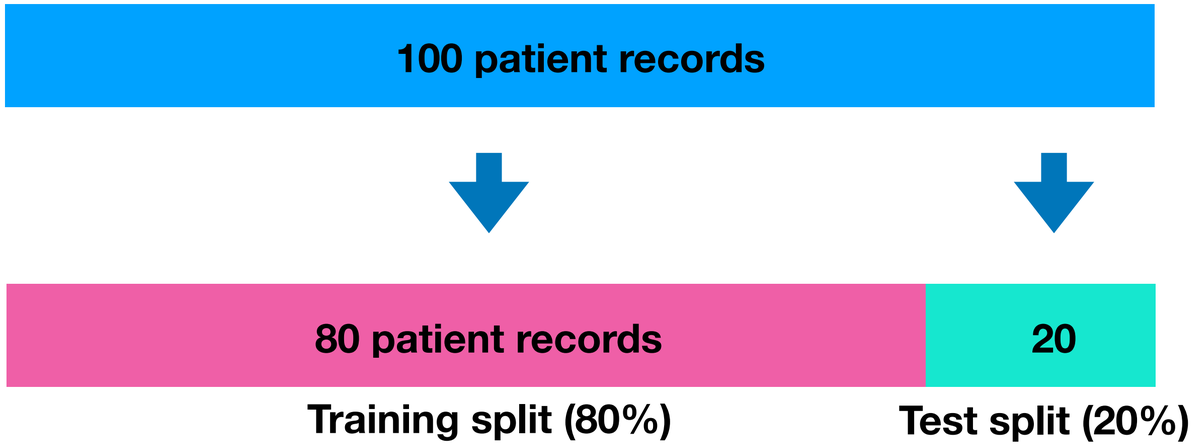

Figure 1.0: Model is trained on training data, and evaluated on the test data.

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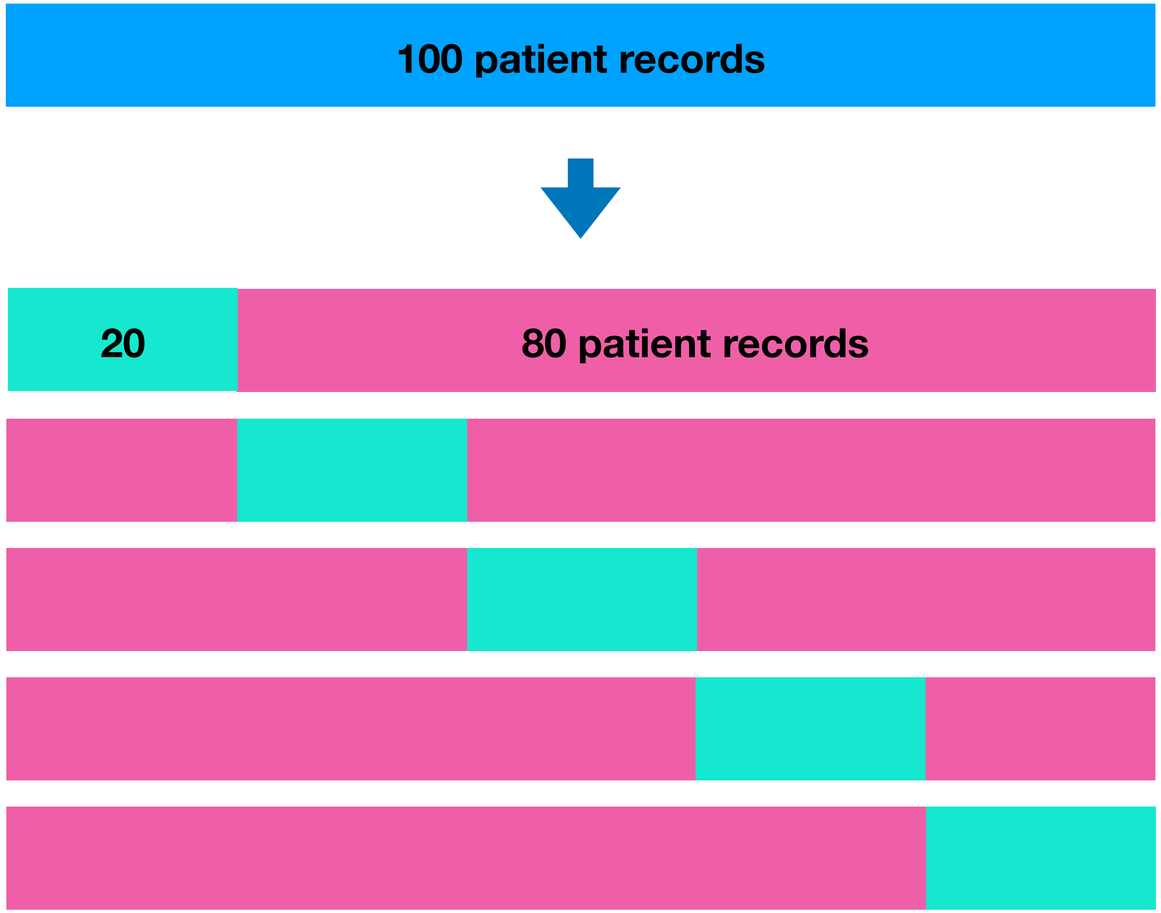


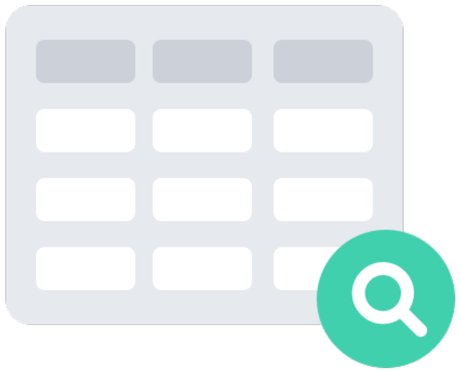
Figure 2.0: Model is trained on training data, and evaluated on the test data.

Things to remember

- All data should be numerical
- There should be no missing values
- Manipulate the test set the same as the training set
- Never test on data you've trained on
- Tune hyperparameters on validation set OR use cross-validation
- One best performance metric doesn't mean the best model

What is structured data?

Data

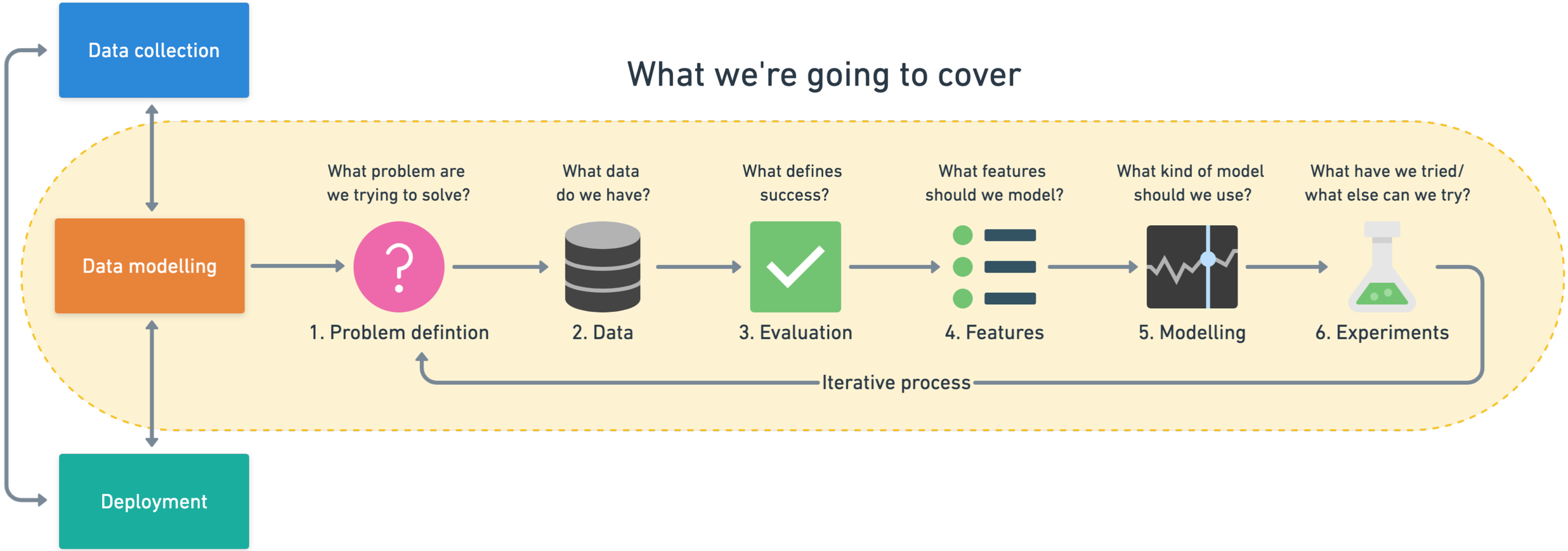


Feature variables | Target

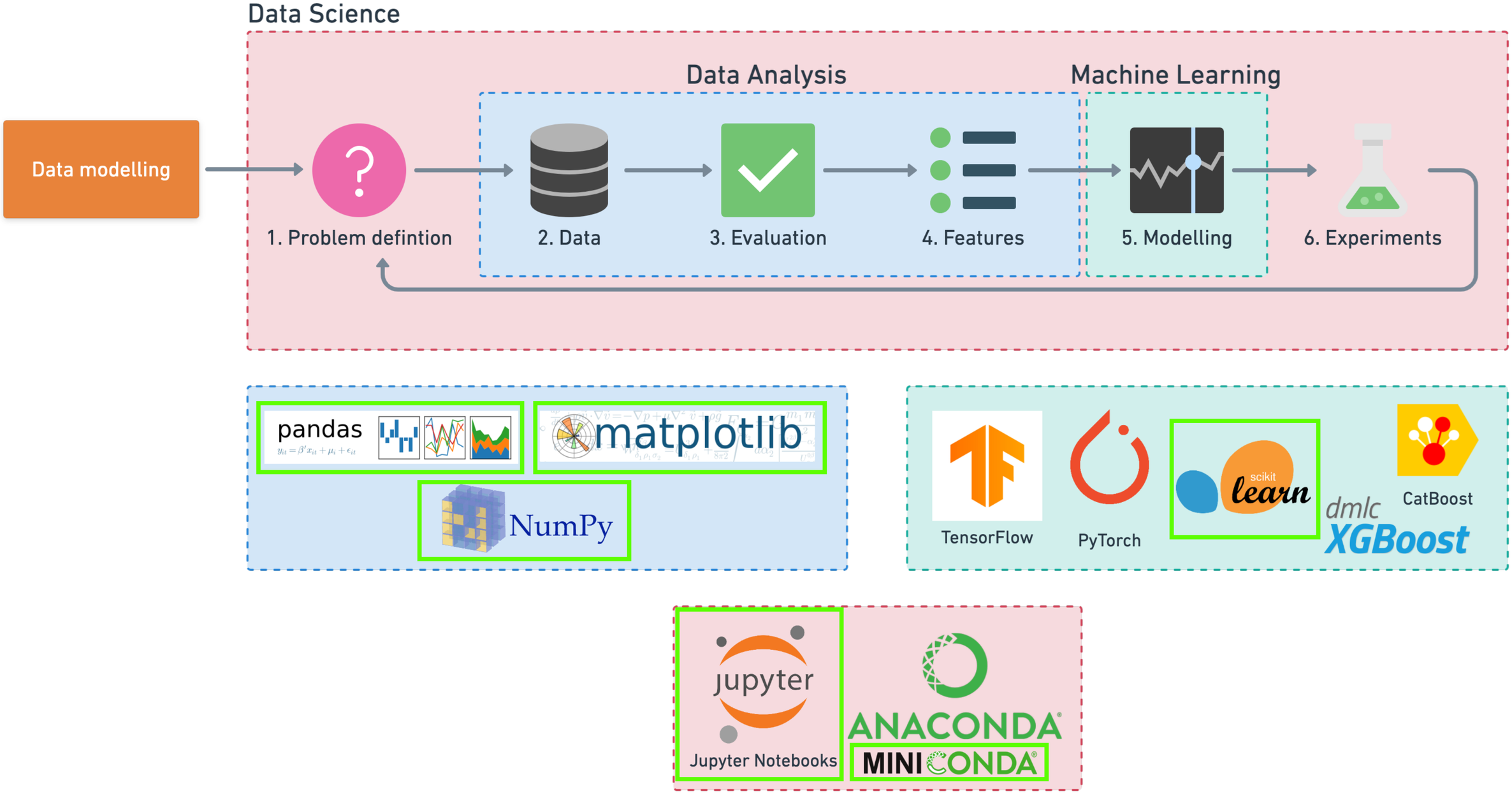
ID	Weight	Sex	Heart Rate	Chest pain	Heart disease?
4326	110Kg	M	81	4	Yes
5681	64Kg	F	61	1	NO
7911	81Kg	M	57	0	NO

Table 1.0: Patient records

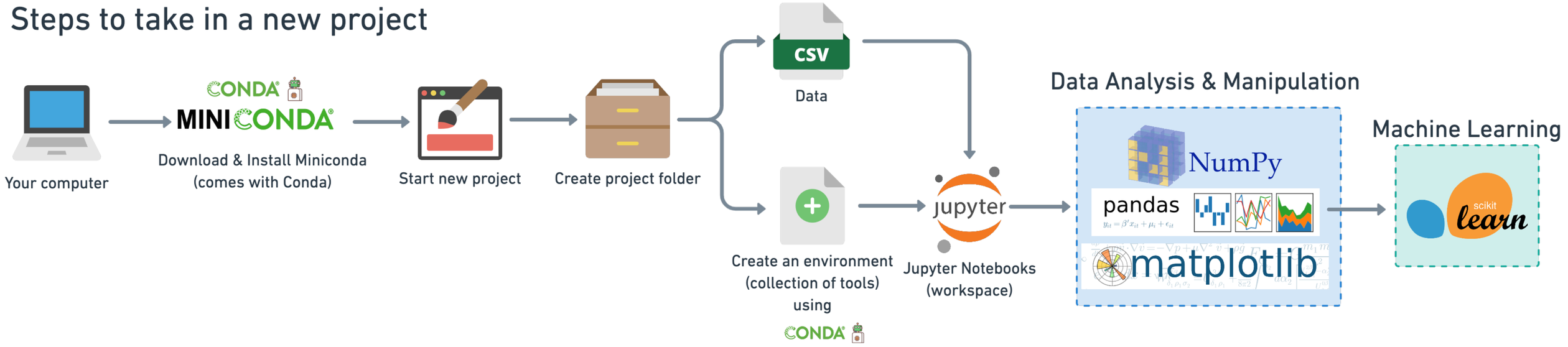
Steps in a full machine learning project



Tools you can use



Steps to take in a new project



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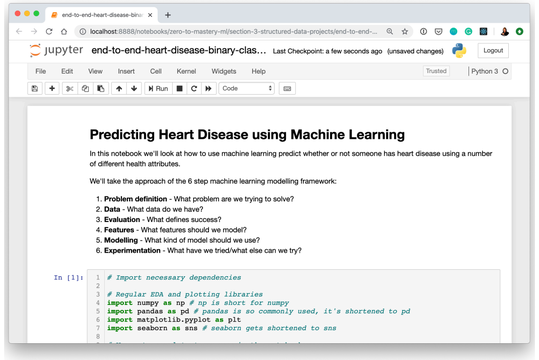

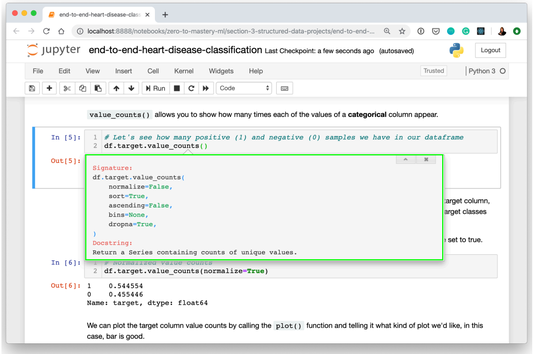

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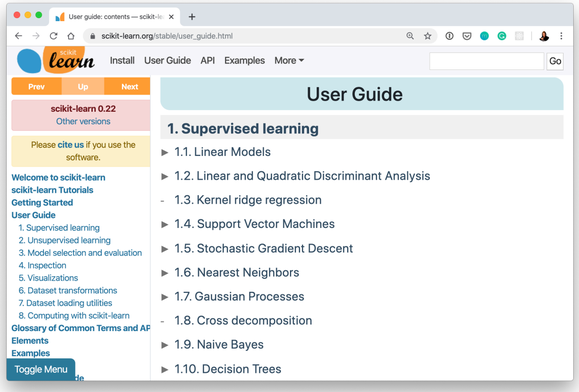

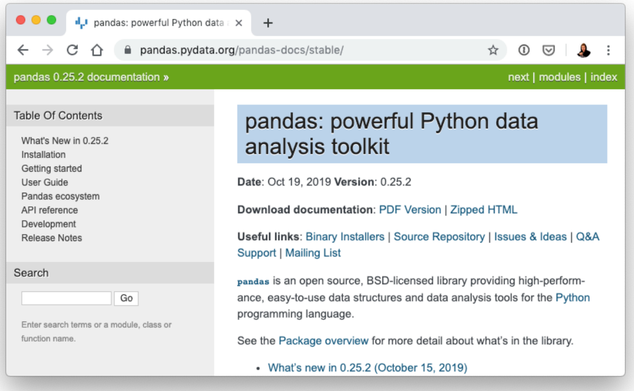

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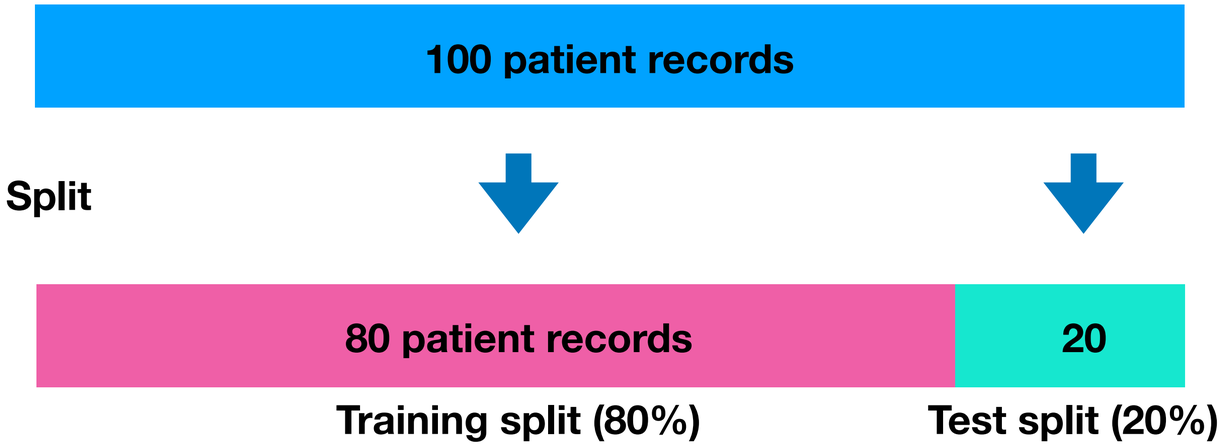

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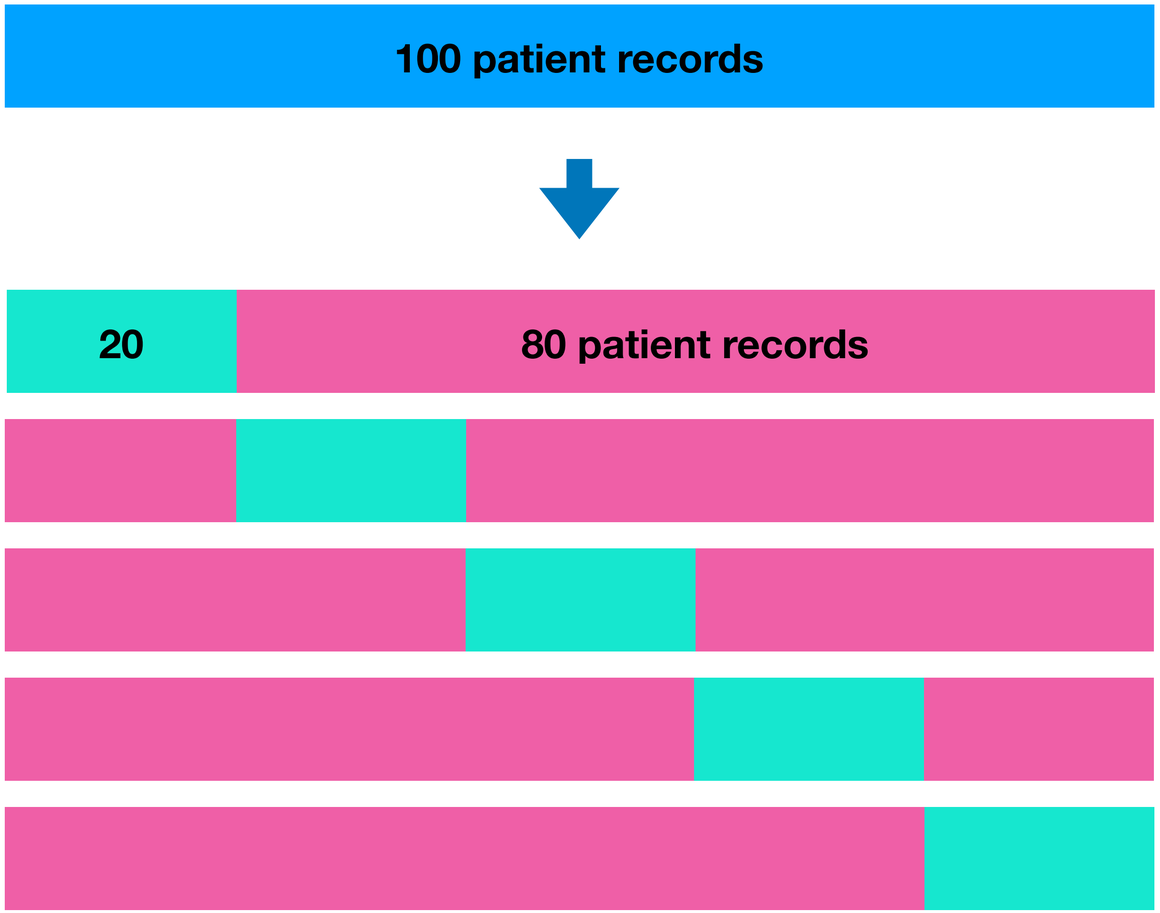

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Classification and Regression metrics

Classification	Regression
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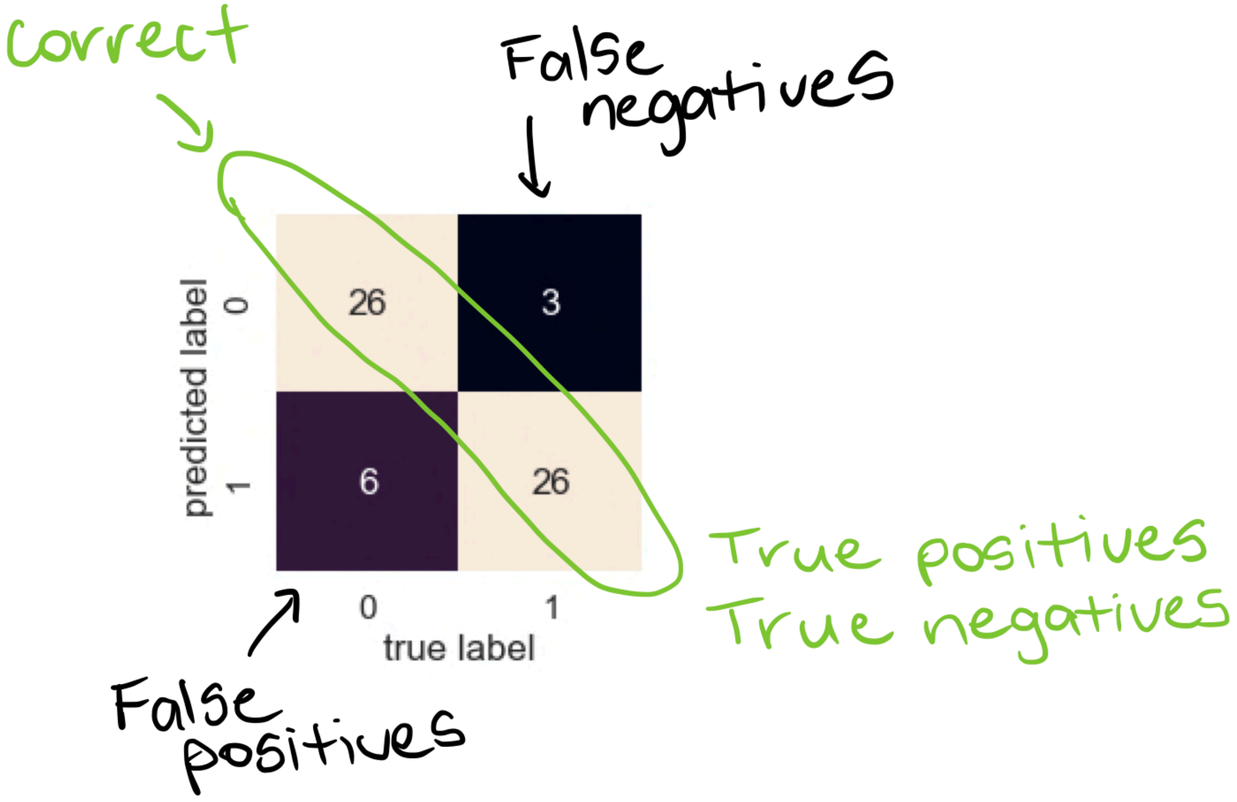

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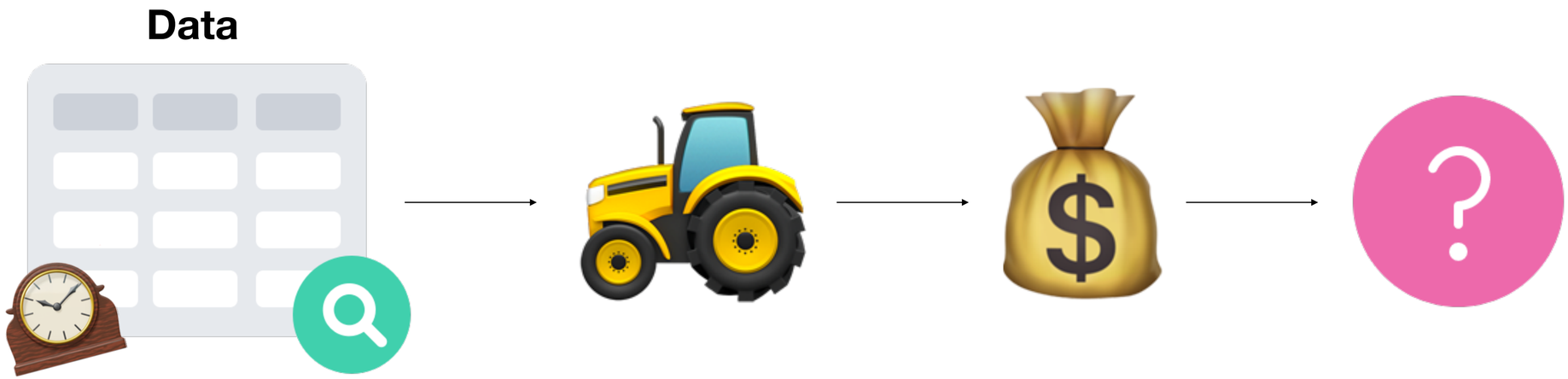
Structured Data Project 2: Predicting the sale price of Bulldozers (regression)



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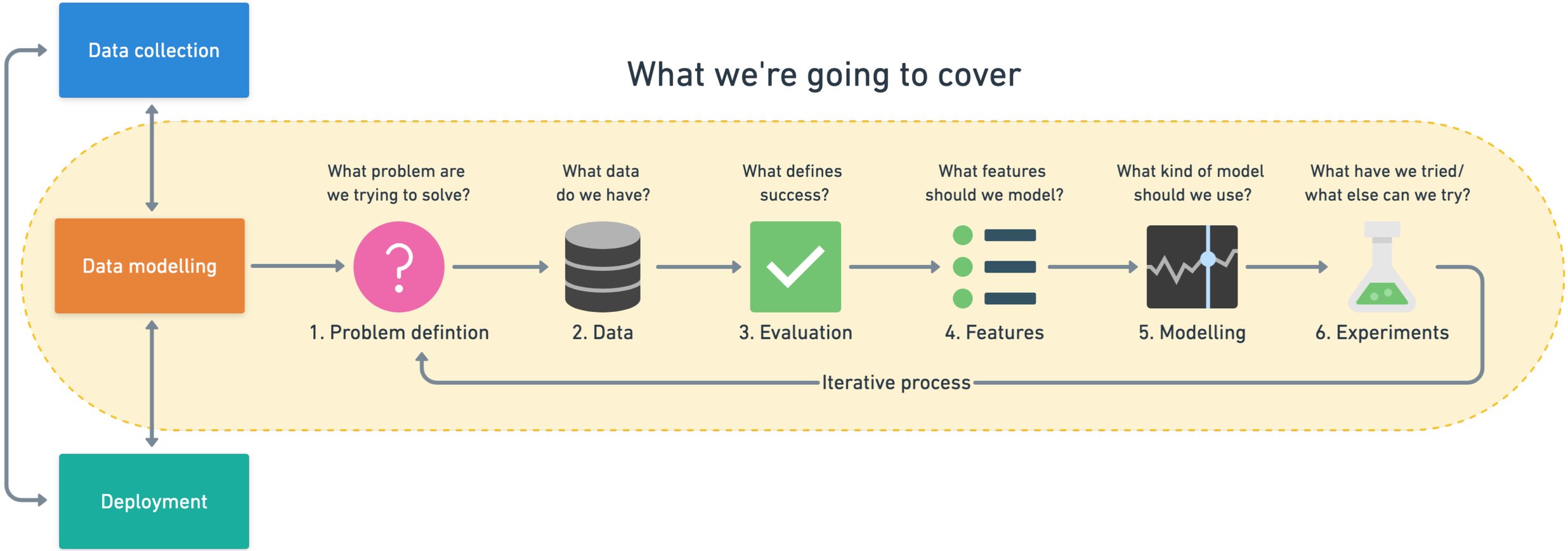

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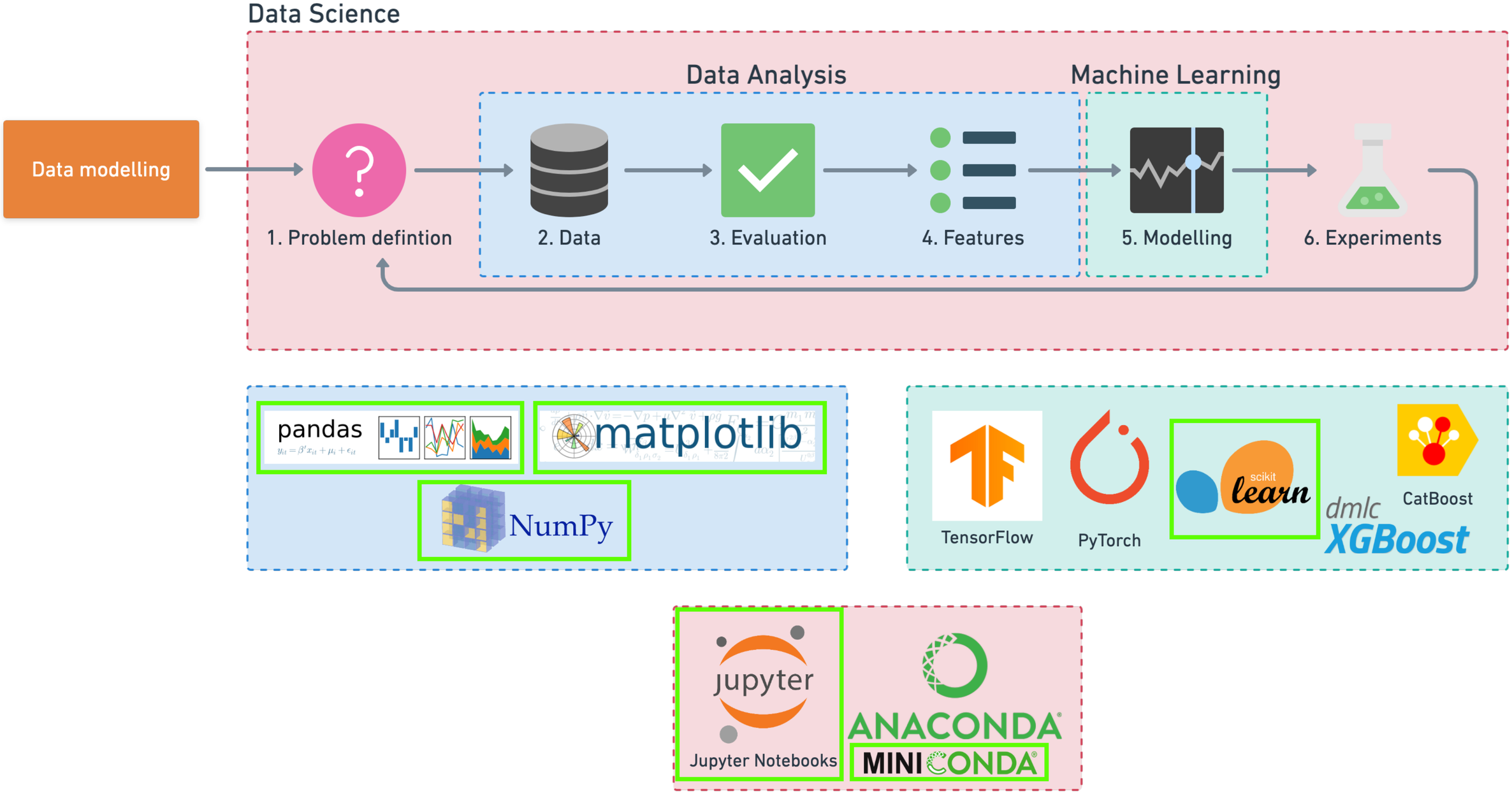

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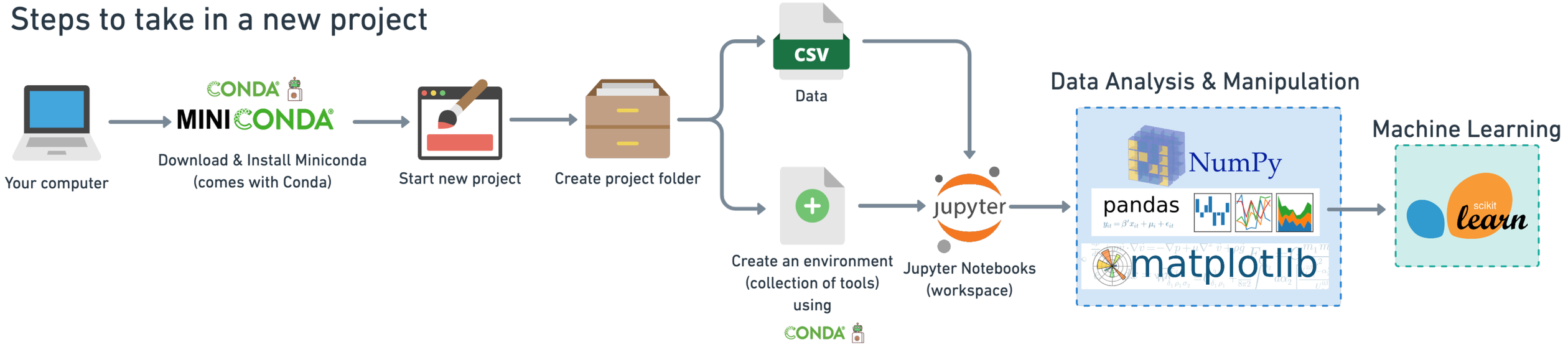

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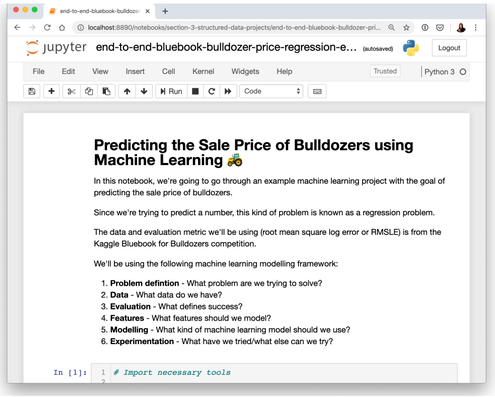

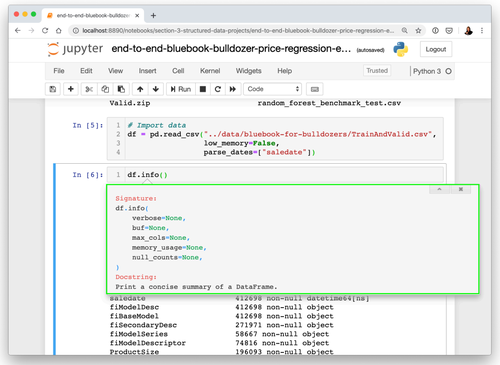

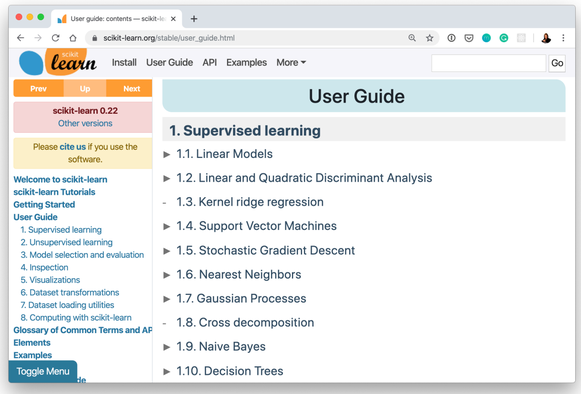

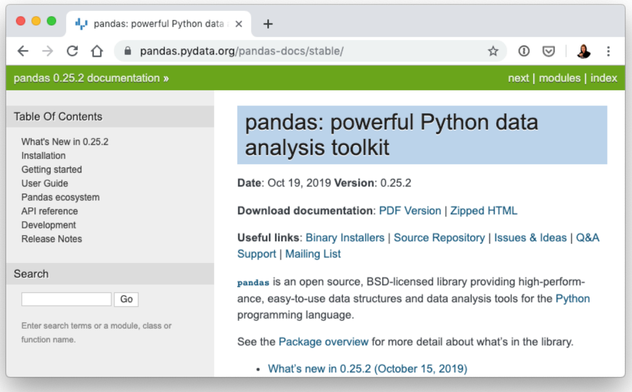

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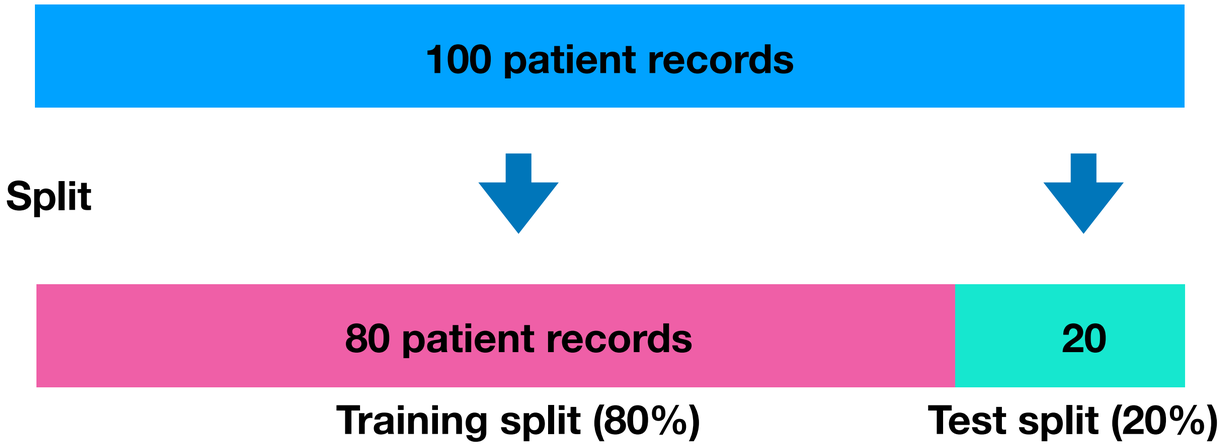

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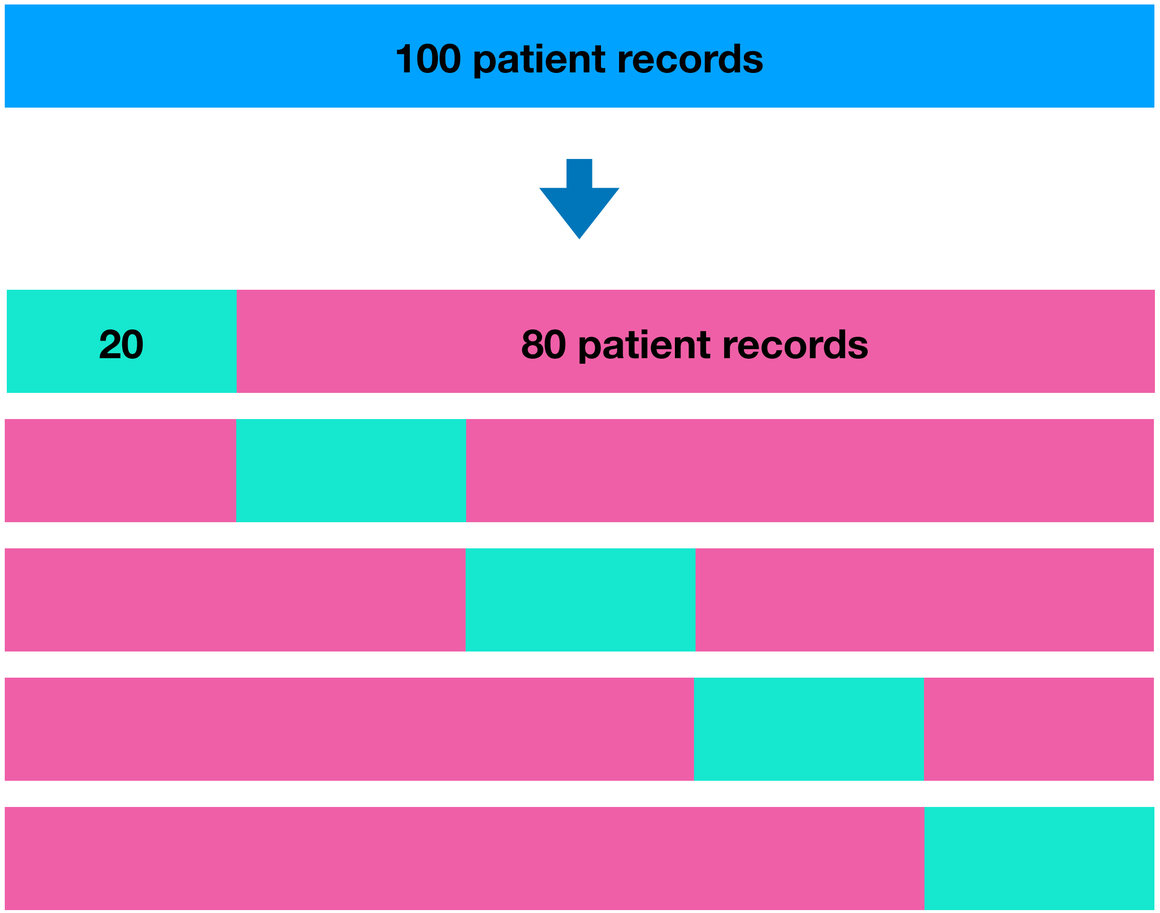

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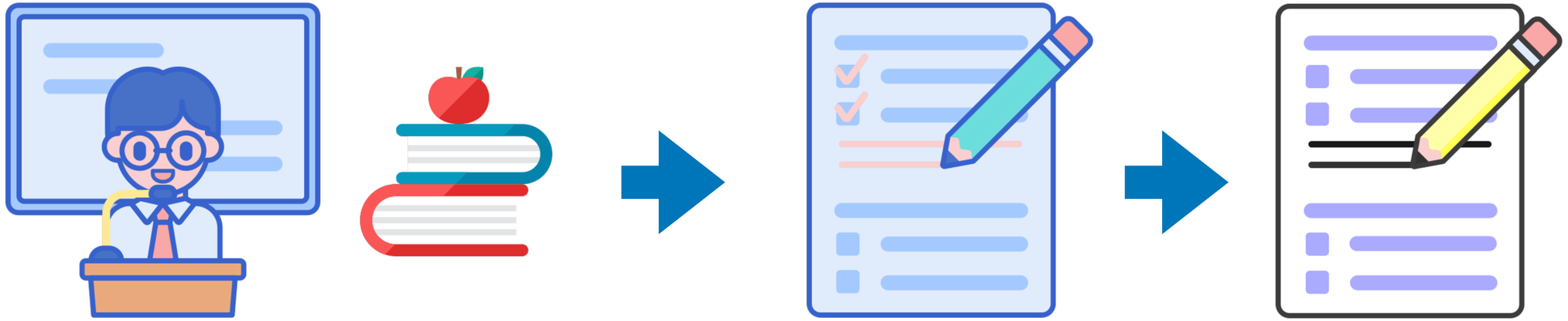

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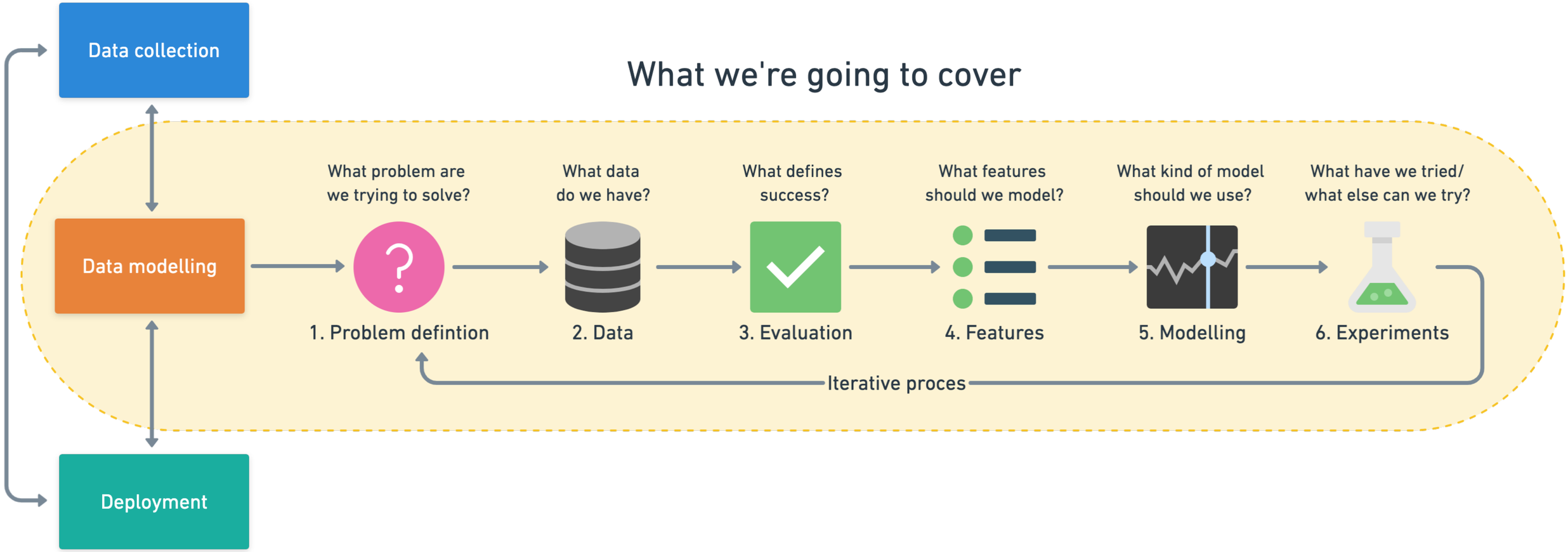
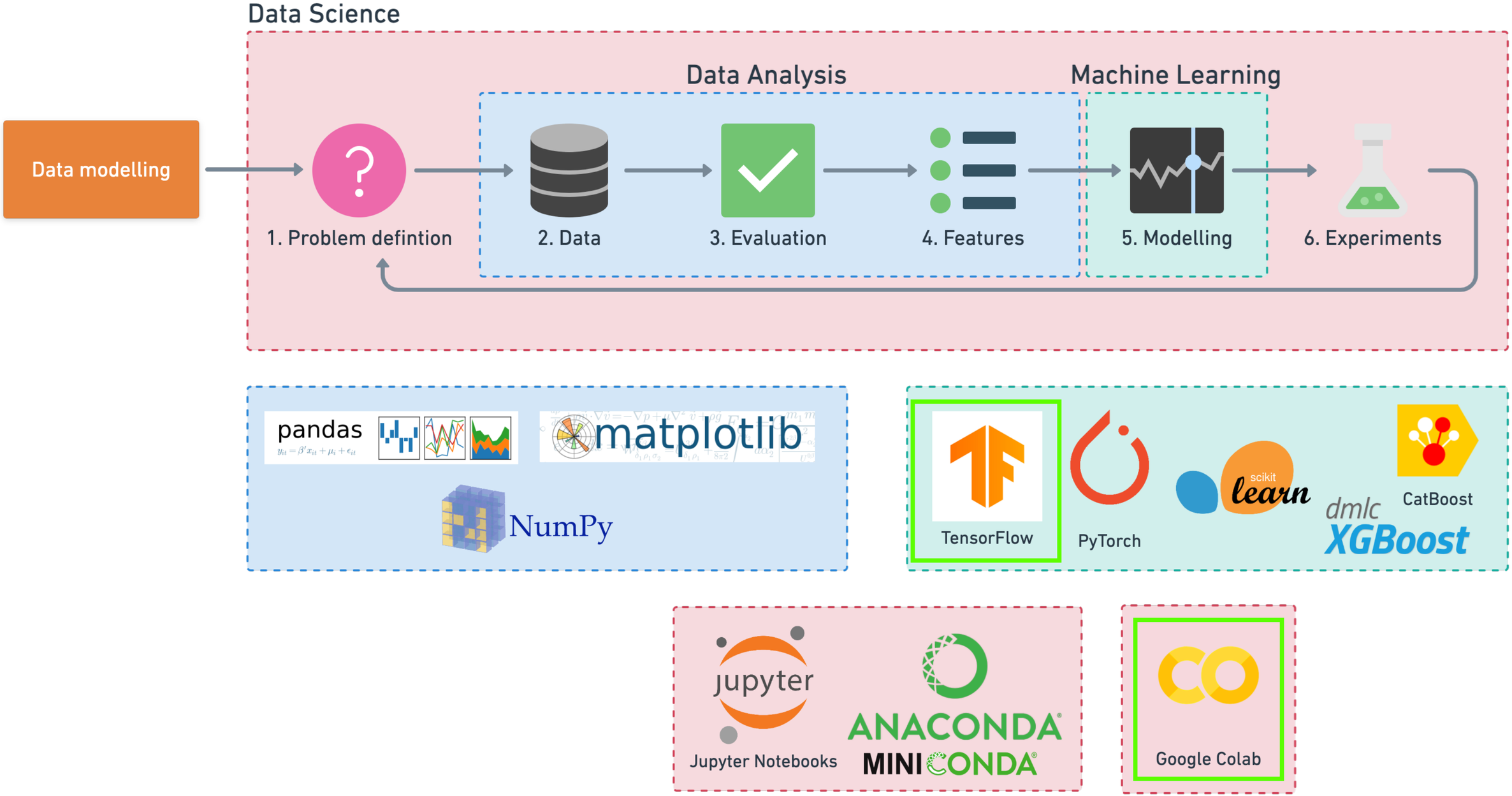
- **MAE** gives a better indication of how far off each of your model's predictions are on average.
- As for **MAE** or **MSE**, because of the way MSE is calculated, squaring the differences between predicted values and actual values, it amplifies larger differences. Let's say we're predicting the value of houses (which we are).
  - Pay more attention to MAE: When being $10,000 off is ***twice*** as bad as being $5,000 off.
  - Pay more attention to MSE: When being $10,000 off is ***more than twice*** as bad as being $5,000 off.

Steps in a full machine learning project

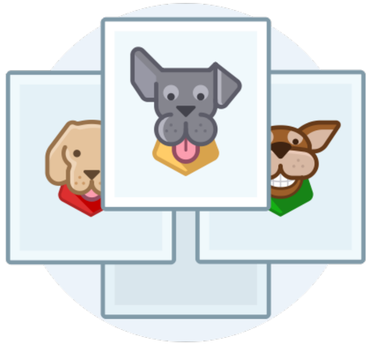


Tools you can use



A new contender!

What is TensorFlow?



From: daniel@mrdbourke.com
Hey Daniel,

First of all, this machine learning course is incredible!
I can't wait to use what I've learned!

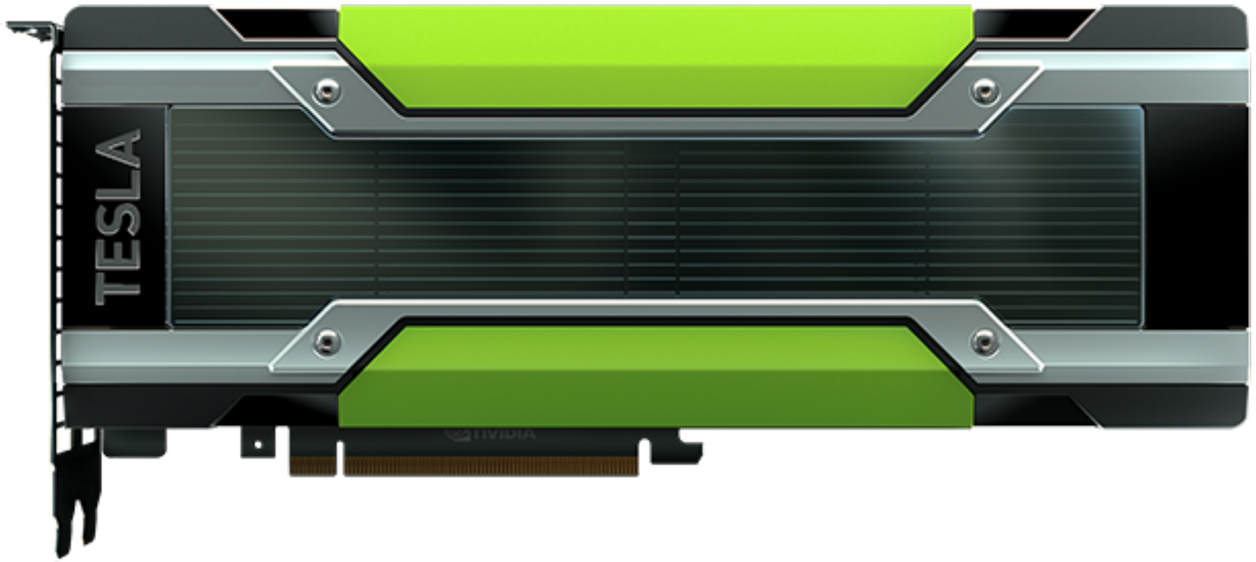
Unstructured

?

Why TensorFlow?

- Write fast deep learning code in Python (able to run on a GPU)
- Able to access many pre-built deep learning models
- Whole stack: preprocess, model, deploy
- Originally designed and used in-house by Google (now open-source)

What is a GPU?



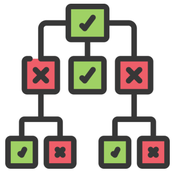
Choosing a model (throwback)

Problem 1 (structured)

Model 1

Structured Data

CatBoost



Random Forest

Problem 2 (unstructured)

Model 2

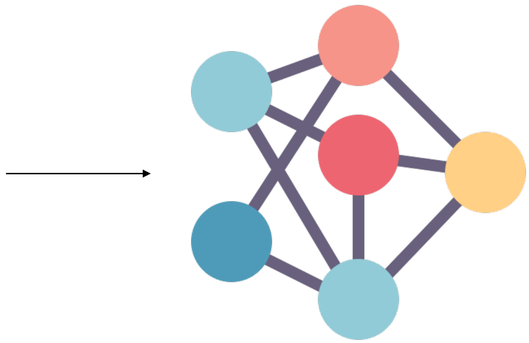
Unstructured Data

Deep Learning

Transfer Learning

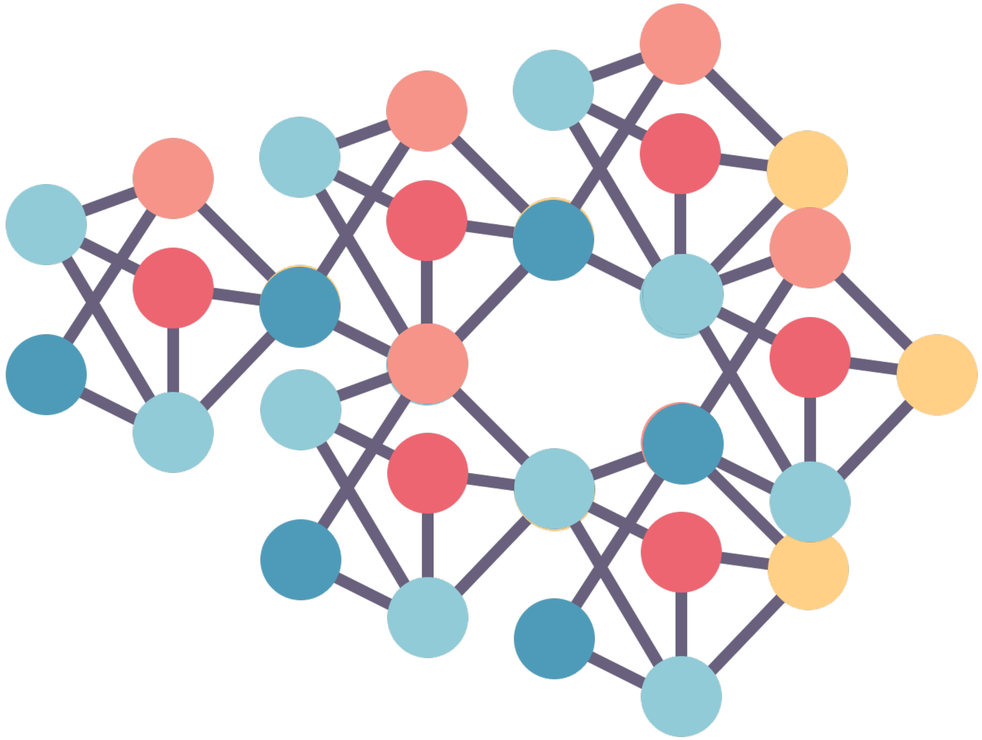
TensorFlow Hub

What is deep learning? What are neural networks?



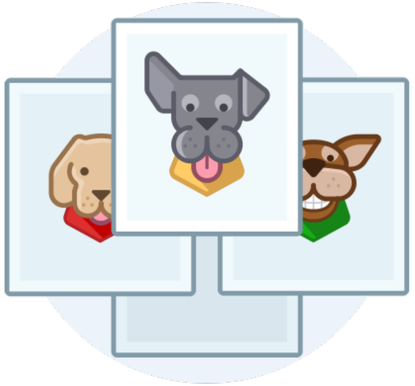
Labrador

What is deep learning? What are neural networks?



Labrador

What kind of deep learning problems are there?



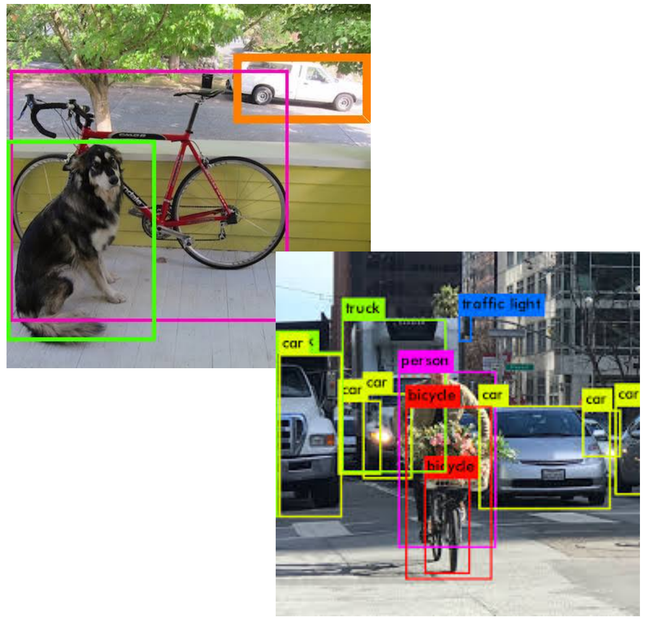
From: daniel@mrdbourke.com
Hey Daniel,

First of all, this machine learning course is incredible!
I can't wait to use what I've learned!

Classification

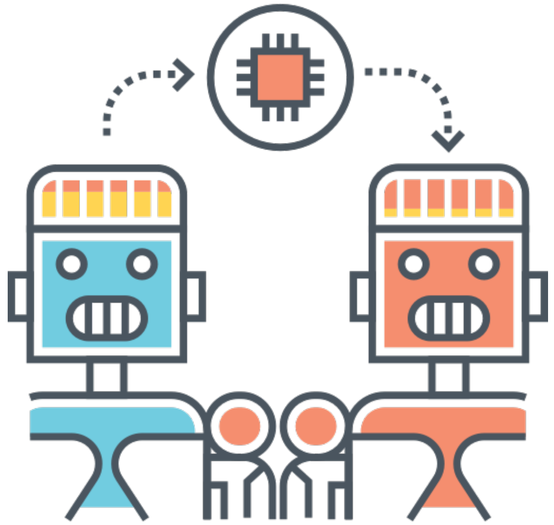
Hey Siri, where's the nearest cafe?

Sequence to sequence (seq2seq)



Object detection

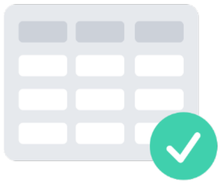
What is transfer learning? Why use transfer learning?



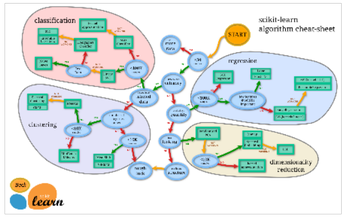
- Take what you know in one domain and apply it to another.
- Starting from scratch can be expensive and time consuming.
- Why not take advantage of what's already out there?

What are we going to cover?

A Scikit-Learn workflow



1. Get data ready



2. Pick a model
(to suit your problem)

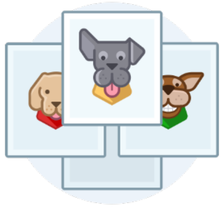
3. Fit the model to the data
and make a prediction

4. Evaluate the model

5. Improve through
experimentation

6. Save and reload
your trained model

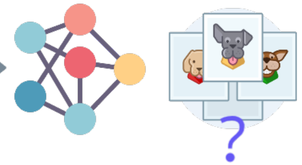
A TensorFlow workflow



1. Get data ready
(turn into Tensors)

TensorFlow
Hub

2. Pick a model
(to suit your problem)



3. Fit the model to the data
and make a prediction

4. Evaluate the model

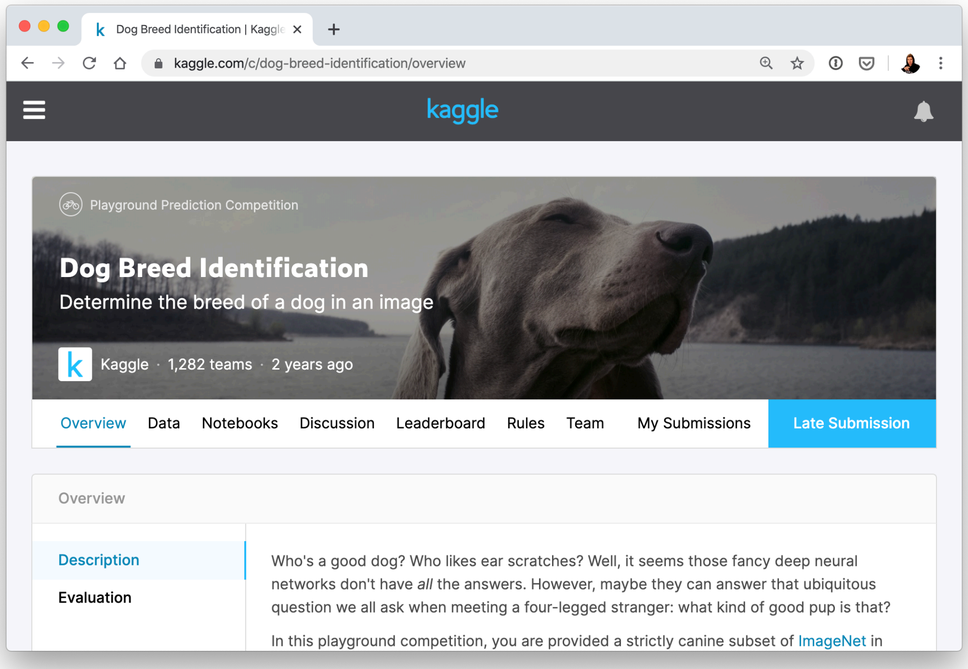
5. Improve through
experimentation

6. Save and reload
your trained model

What are we going to cover?

- An end-to-end multi-class classification workflow with TensorFlow
- Preprocessing image data (getting it into Tensors)
- Choosing a deep learning model
- Fitting a model to the data (learning patterns)
- Making predictions with a model (using patterns)
- Evaluating model predictions
- Saving and loading models
- Using a trained model to make predictions on custom data

The problem we're going to work on

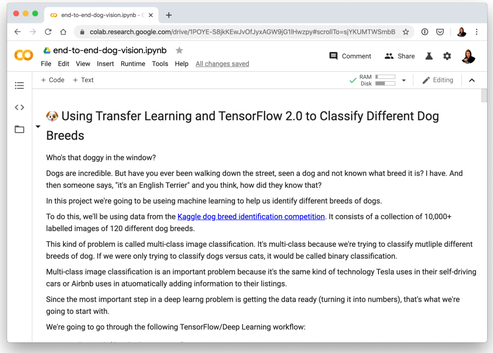


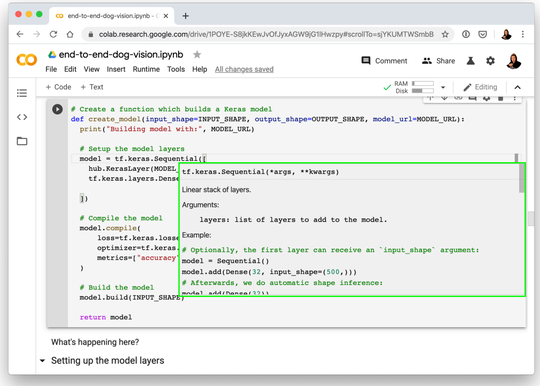
Classification

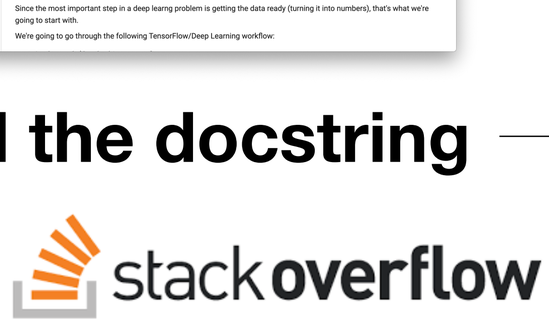
- "Is this example one thing or another?"
- Binary classification = two options
- Multi-class classification = more than two options

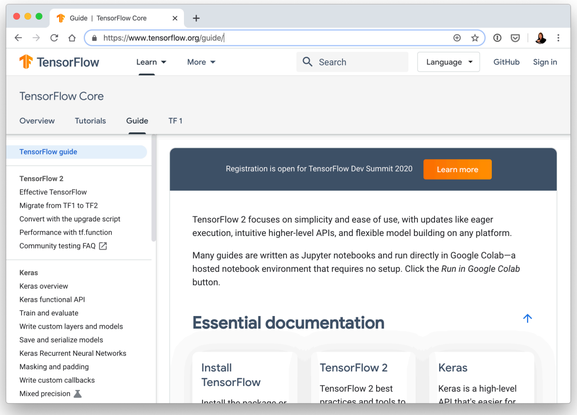
Where can you get help?

- Follow along with the code
- Try it for yourself
- Press SHIFT + CMD + SPACE to read the docstring
- Search for it
- Try again
- Ask (don't forget the Discord chat!)

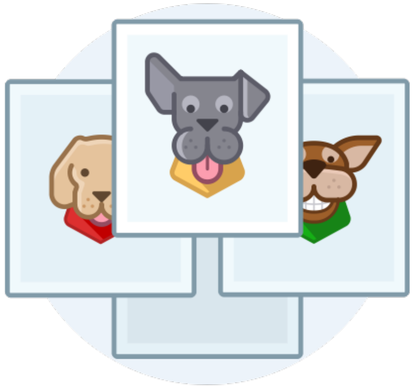








Let's find those doggos!



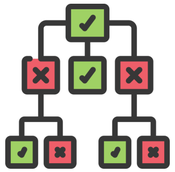
Choosing a model (throwback)

Problem 1 (structured)

Model 1

Structured Data

CatBoost



Random Forest

Problem 2 (unstructured)

Model 2

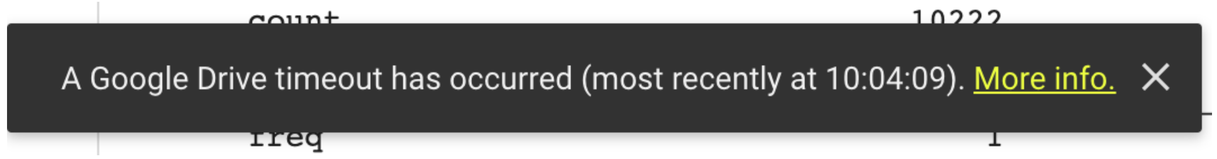
Unstructured Data

Deep Learning

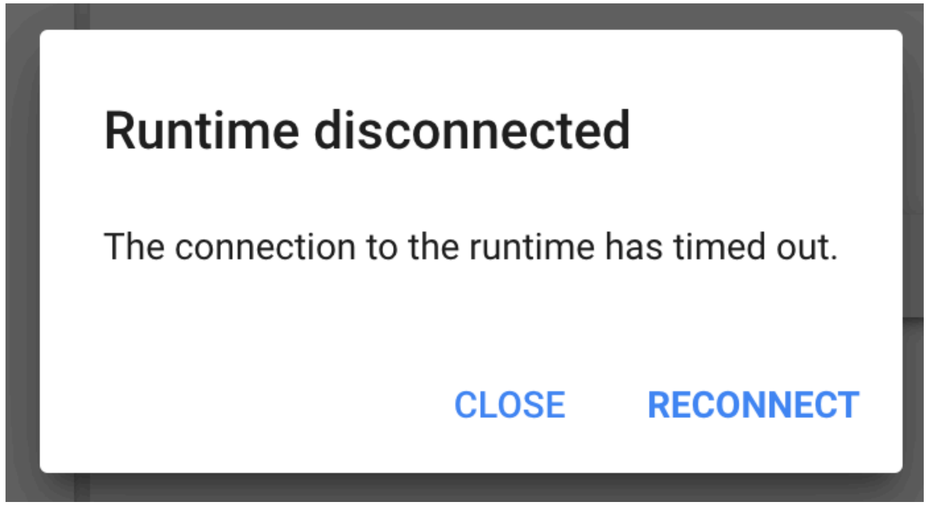
Transfer Learning

TensorFlow Hub

Things you might see in Colab



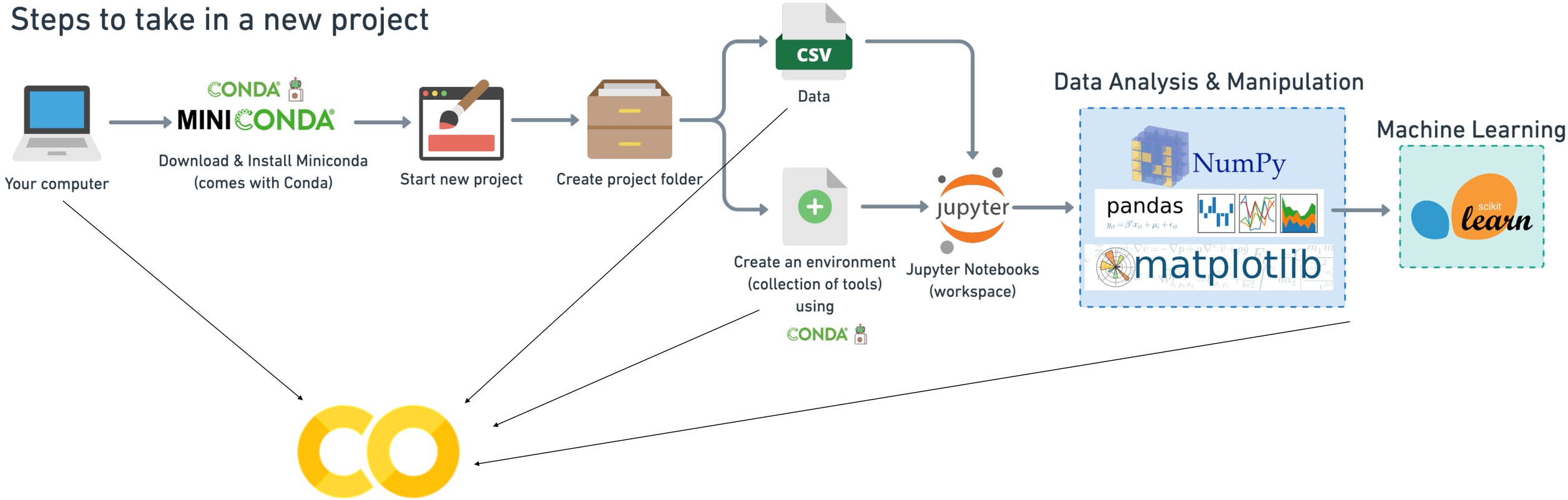
Usually fixes itself, may need to reconnect Google Drive to Colab.



A Colab connection will sometimes drop out (it's hard to tell when). If it does, you'll need to reconnect and potentially rerun all of your cells (disconnecting = variables lost).

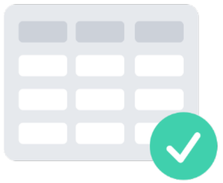
For more information and fixes, refer to the Google Colab FAQ: https://research.google.com/colaboratory/faq.html

Steps to take in a new project



What are we going to cover?

A Scikit-Learn workflow



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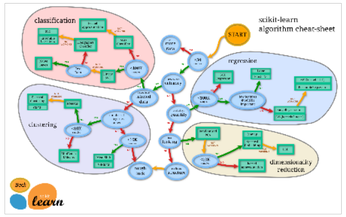

2. Pick a model
(to suit your problem)

3. Fit the model to the data
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4. Evaluate the model

5. Improve through
experimentation

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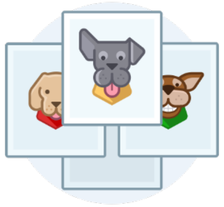
your trained model

A TensorFlow workflow



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(turn into Tensors)

TensorFlow
Hub

2. Pick a model
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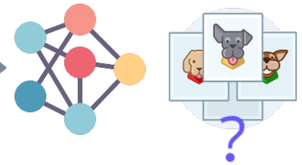

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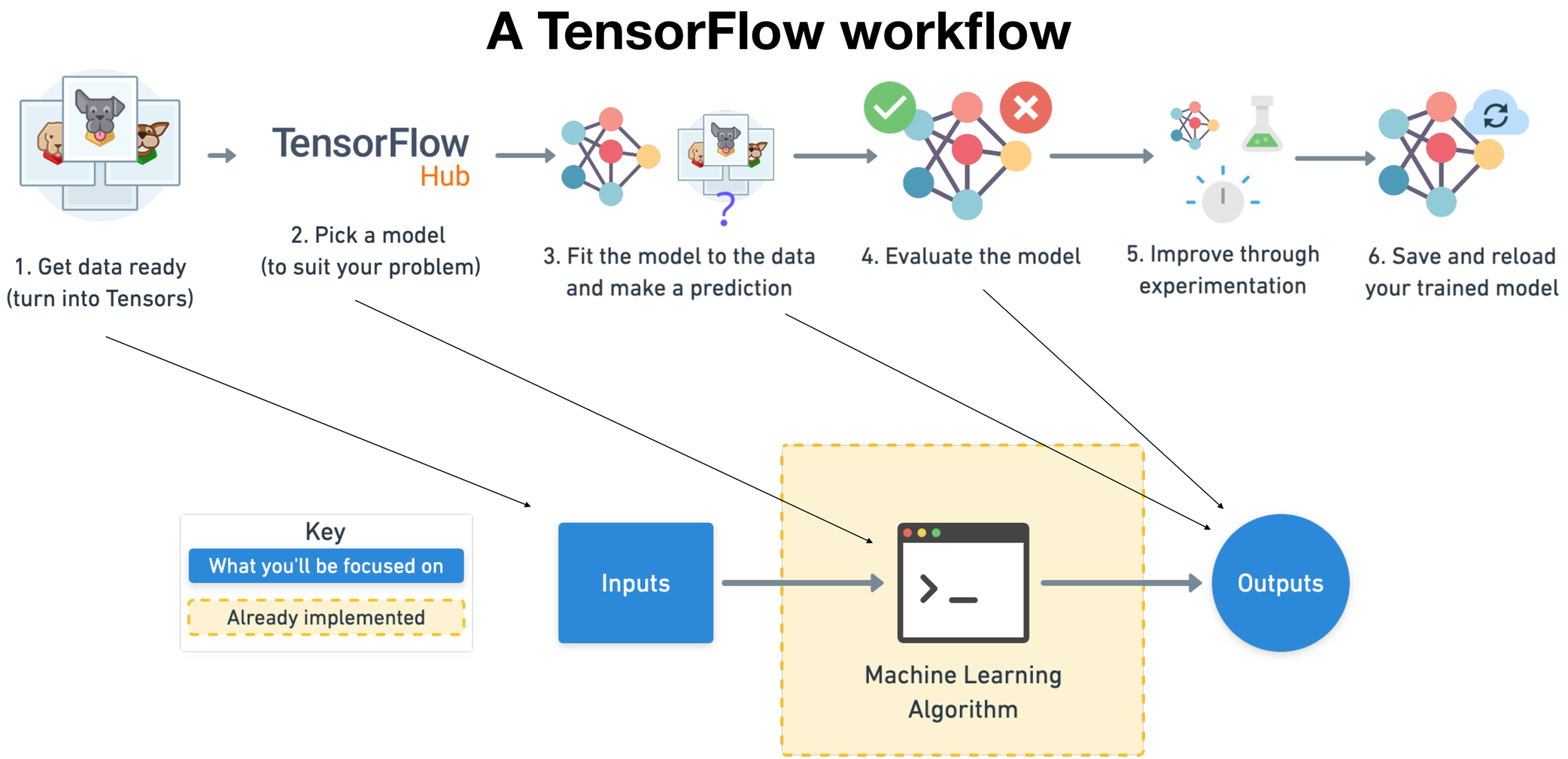
What we're focused on

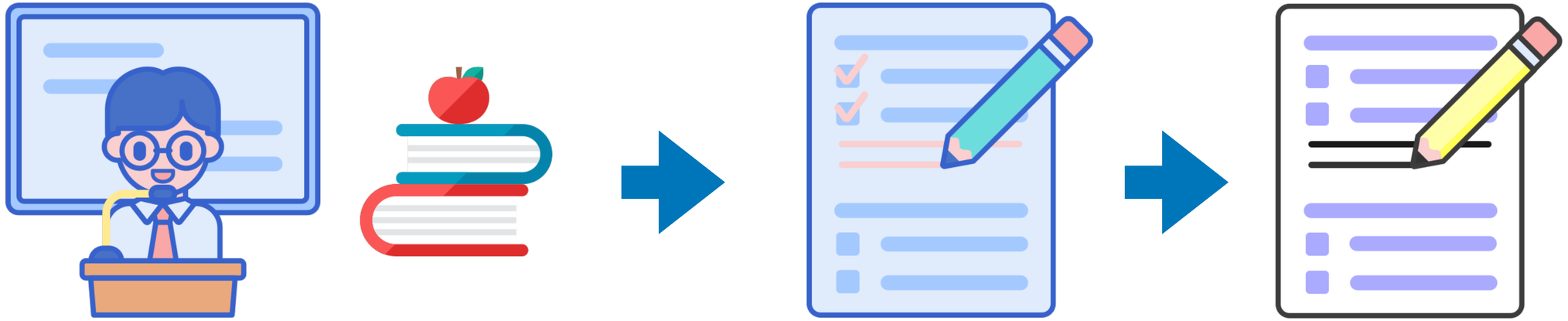


Which activation? Which loss?

Binary classification	Multi-class classification
Activation: Sigmoid	Activation: Softmax
Loss: Binary Crossentropy	Loss: Categorical Crossentropy

The most important concept in machine learning

(the 3 sets)



Course materials (training set)

Practice exam (validation set)

Final exam (test set)

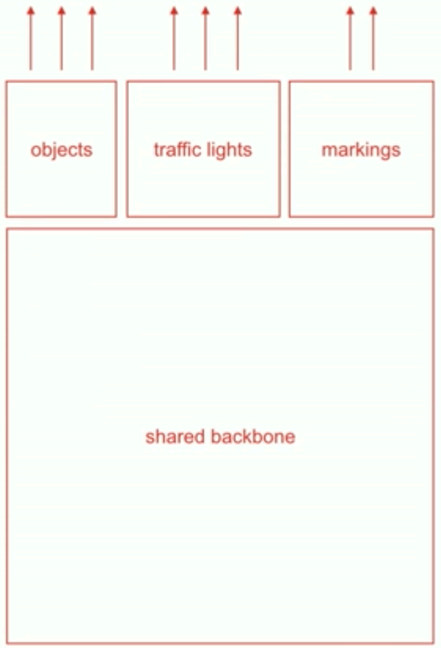
Generalization

The ability for a machine learning model to perform well on data it hasn't seen before.

Tesla using ResNet50 backbones

SINGLE VIEW TASKS

- (3, 960, 1280) input images
- “ResNet-50 like” dilated backbones
- FPN / DeepLabV3 / UNet -like heads
- ~15 tasks => “prototypes framework”

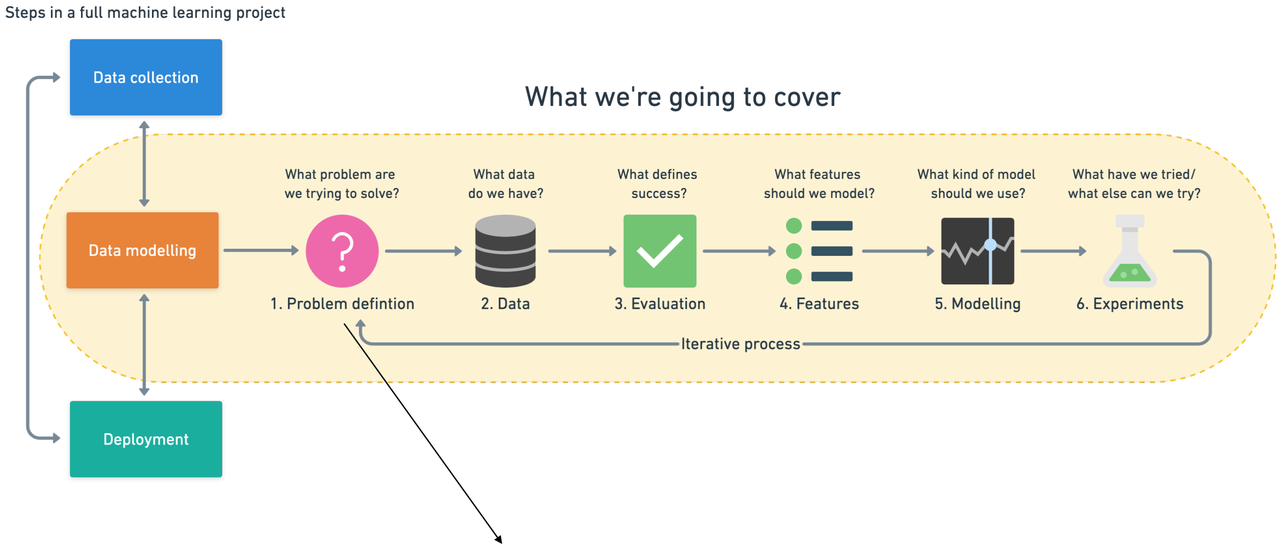


Source: “PyTorch at Tesla by Andrei Karpathy”
https://youtu.be/oBklltKXtDE?t=173

How to think about communicating and sharing your work

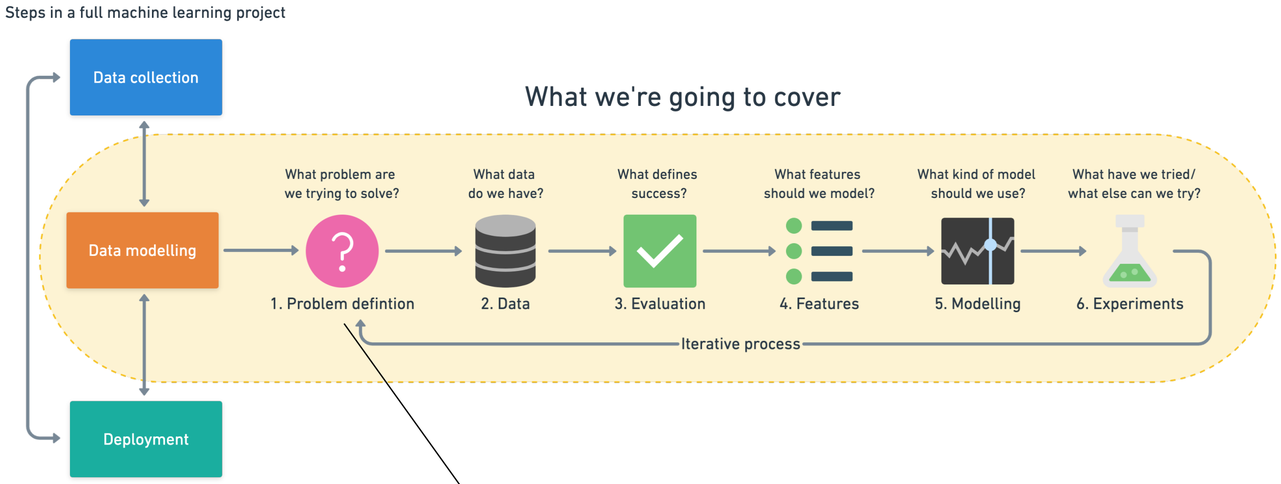
Now you've got skills, what do you do next?

The most important question you can ask



“Who’s it for?”

The most important question you can ask



“Who’s it for?”

What questions will they have?

What needs do they have?

What concerns can you address before they arise?

Heard but not understood

Heard and (potentially) understood

Who’s it for?

People on your team	People outside your team
Boss	Clients
Project manager	Customers
Teammates	Fans

Communicating with people on your team

People on your team	People outside your team
Boss	Clients
Project manager	Customers
Teammates	Fans

“Who’s it for?” → **“What do they need to know?”** →

How the project is going

What’s in the way

What you’ve done

What you’re doing next

Why you’re doing something next

Who else could help

What’s not needed

Where you’re stuck

What’s not clear

What questions do have

Are you still working towards the right thing

Is there any feedback or advice

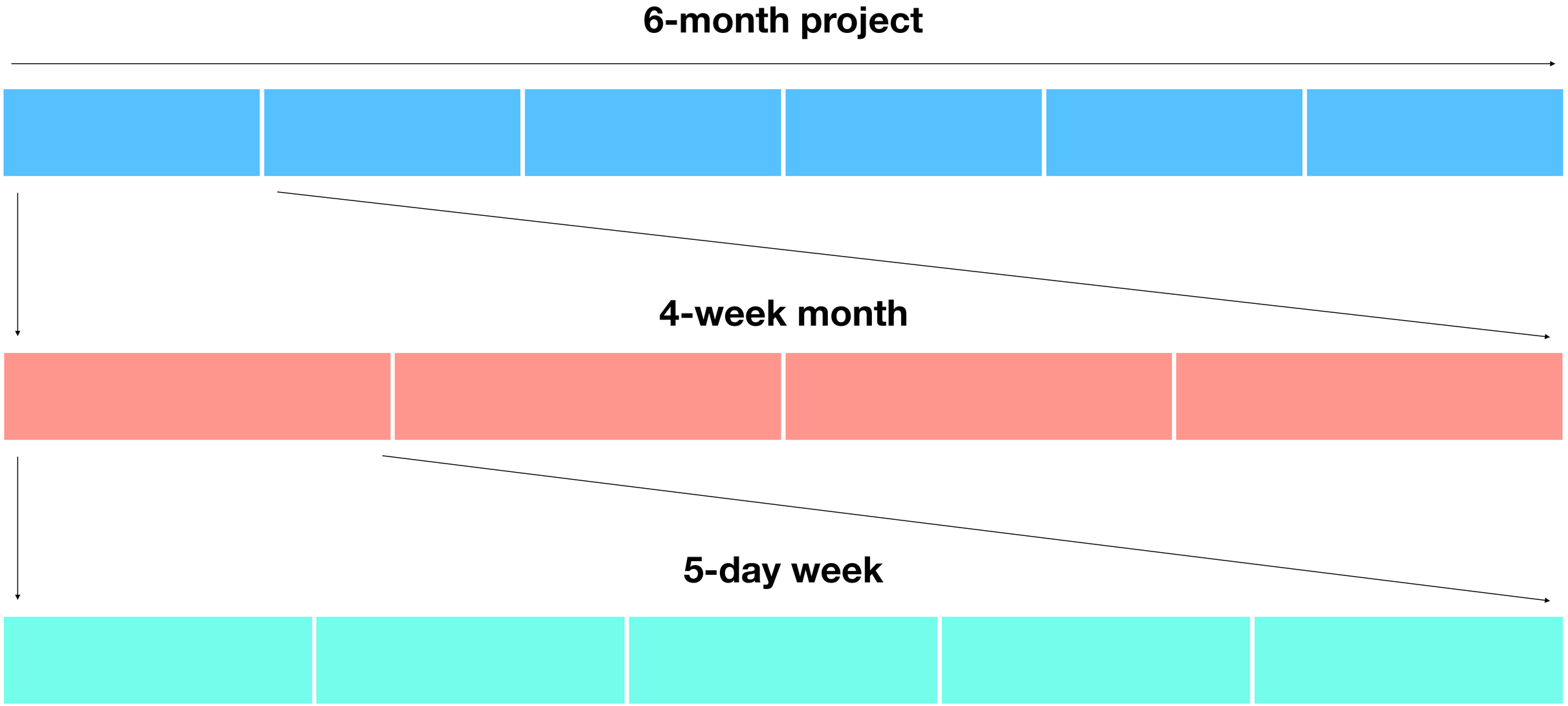
The Project Manager, Boss, Senior, Lead

💰 ✅

⏳ ✅

The People You're Working With, Sitting Next to, in the Group Chat

Break it down



What did you work on today?

What I worked on today (1-3 points on what you did):

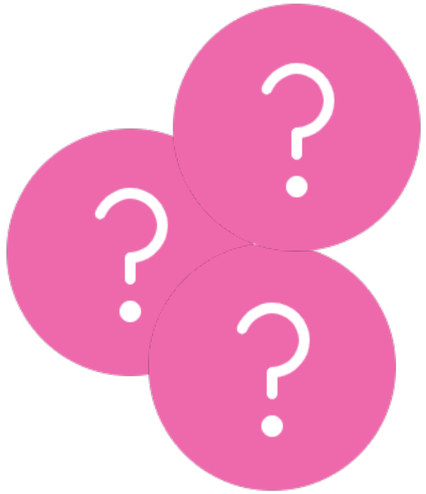
- What's working?
- What's not working?
- What could be improved?

What I'm working on next:

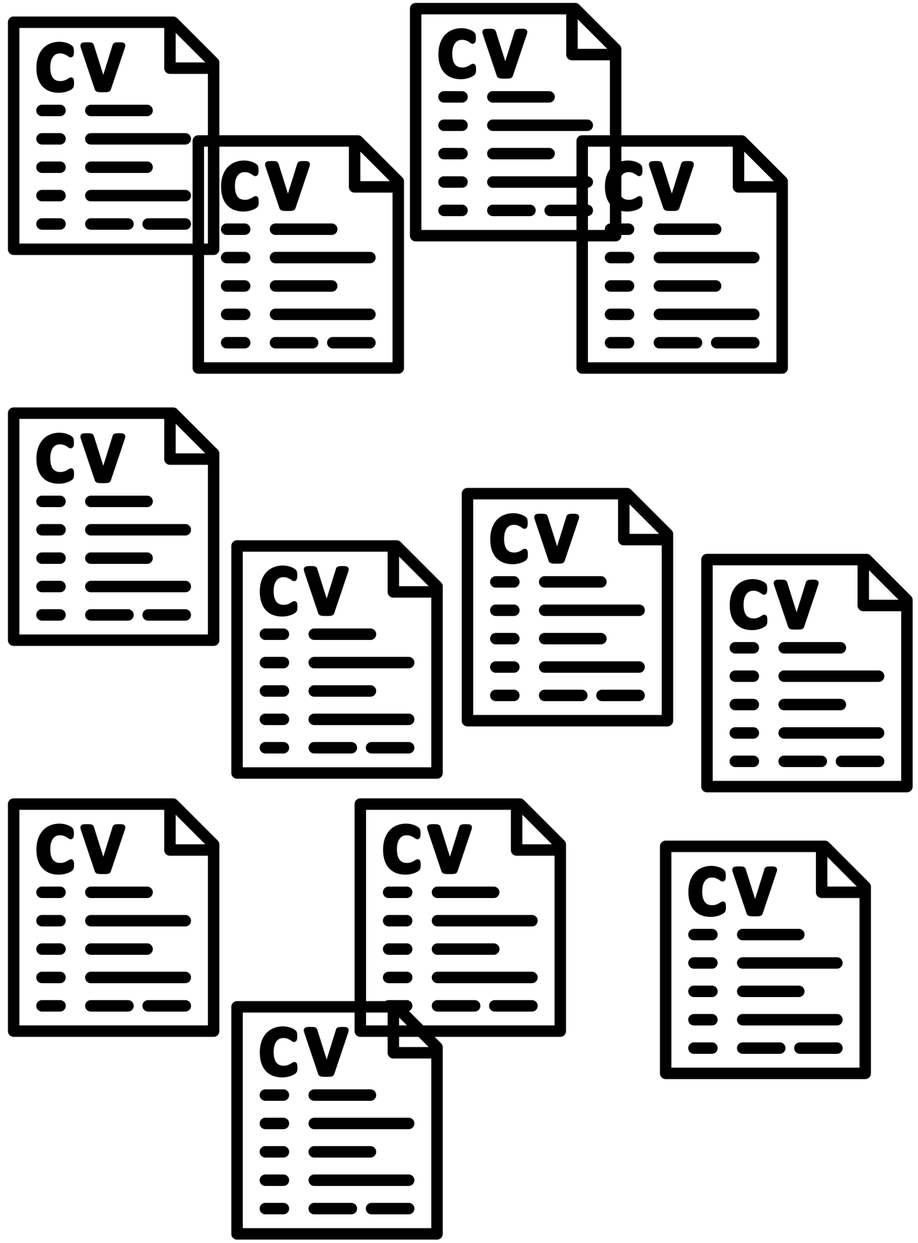
- What's your next course of action? (based on the above)
- Why?
- What's holding you back?

Relate back to overall project goal

Take note of overlaps



Start the job before you have it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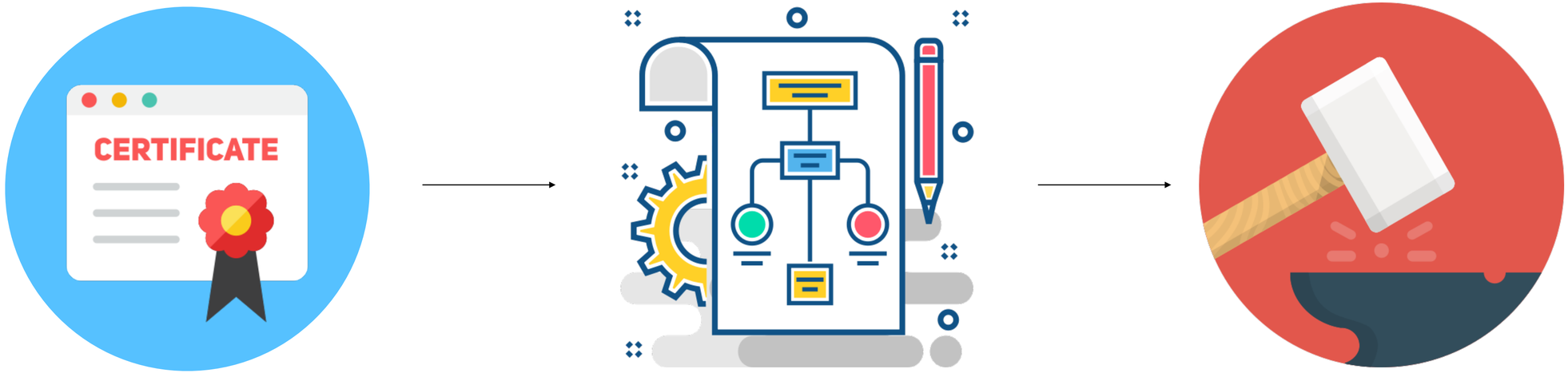
The weekend project principle



(what you work on in your own time)


CV


CV

Acme Co.

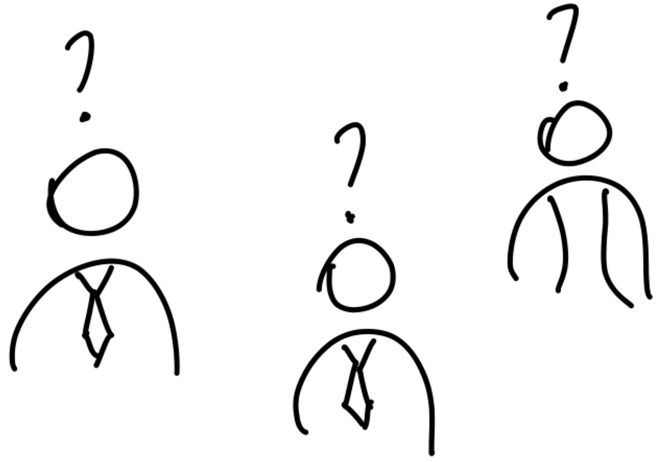
Documented on your blog

6-week project

Communicating with people outside your team

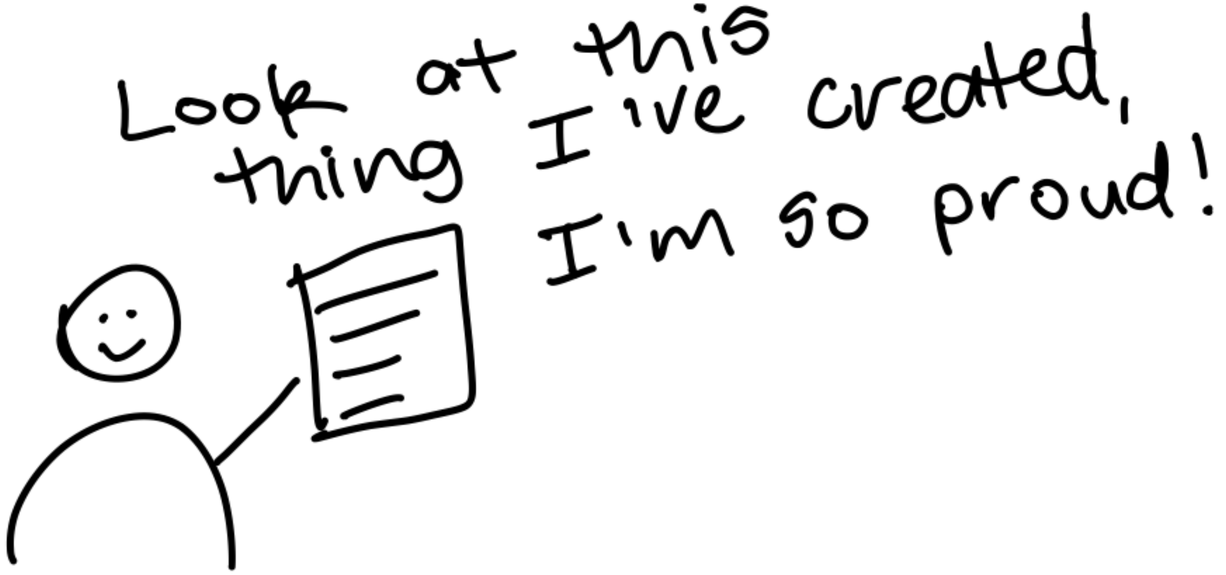
People on your team	People outside your team
Boss	Clients
Project manager	Customers
Teammates	Fans

Obvious to you, amazing to others

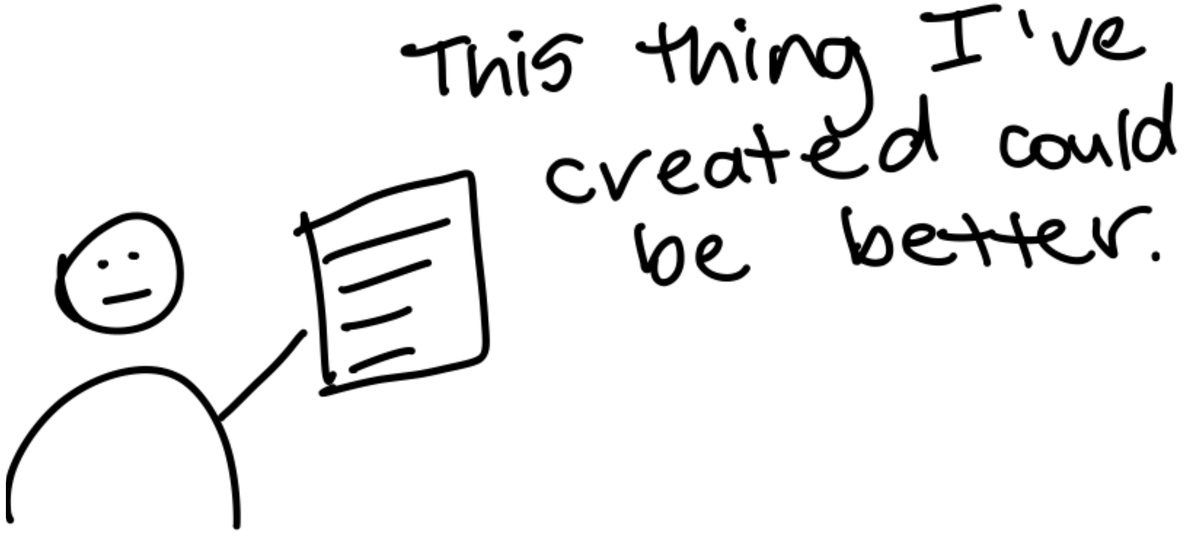


What story are you trying to tell?

You:



Also you:



Always ask, Who's it for?

"Who's it for?" → "What do they need to know?" = Specific = Courage

Write it down

What did you work on today?

What are you working this week?

Progress, not perfection

“Here’s what I’ve done.”