INTRODUCTION TO MACHINE LEARNING





Supervised Learning

Unsupervised Learning

Supervised Learning

Unsupervised Learning

Jupyter Notebook / IDE Python **Programming Language** Conda Package Management Linux* **Operating System**

Conda

Jupyter Notebook / IDE

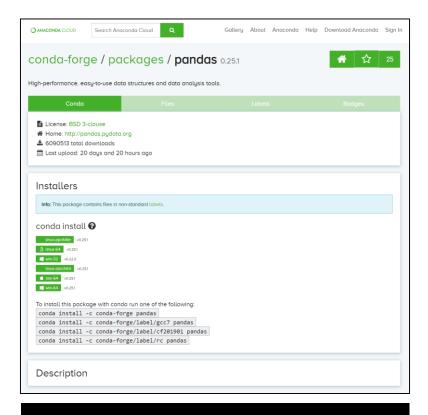
Python
Programming Language

Conda Package Management

Linux*
Operating System

https://conda.io/ https://github.com/conda

- Package Management
 - https://anaconda.org/
 - "You can search and download popular Python and R packages and notebooks to jumpstart your data science work."



\$ conda install pandas

Conda

```
$ cd ~
$ wget https://repo.anaconda.com/miniconda/Miniconda3-latest-Linux-x86_64.sh
$ sh Miniconda3-latest-Linux-x86_64.sh
```

Python

Jupyter Notebook / IDE

Python
Programming Language

Conda
Package Management

Linux*
Operating System























Python

```
$ conda install python
```

Jupyter

Jupyter Notebook / IDE

Python
Programming Language

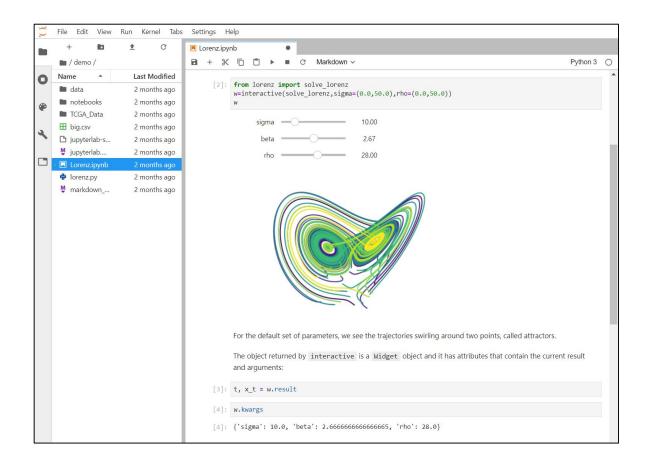
Conda Package Management

Linux*
Operating System

Jupyter

- Web-based development environment
- Notebooks
 - Live code cells
 - Visualizations
 - Text (Markdown)

https://jupyter.org/
https://github.com/jupyter



Jupyter

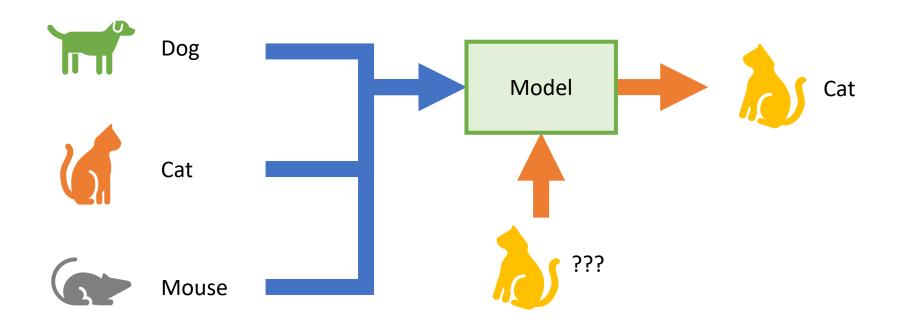
```
$ conda install jupyterlab
$ jupyter lab
```

Supervised Learning

Unsupervised Learning

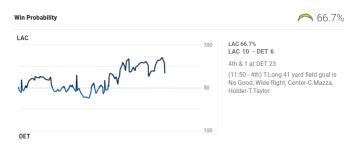
Supervised Learning

Train a model using labeled data



Supervised Learning

- Classification
 - Predicts a class [dog, cat, mouse]
- Binary classification
 - Predicts a binary class [true, false]
- Regression
 - Predict a continuous value



Binary classification



Regression

Heart Disease Example

https://archive.ics.uci.edu/ml/datasets/Heart+Disease https://github.com/sranck/cposc2019/heart.ipynb

- UCI Machine Learning Repository
 - https://archive.ics.uci.edu/ml/datasets/Heart+Disease
- 303 labeled patients
 - 13 features (age, cholesterol, blood pressure, etc.)
 - Is heart disease present? (yes/no)
- Can we predict the presence of heart disease?
 - Binary classification

- age: age in years
- sex: sex
 - 1 = male; 0 = female
- cp: chest pain type
 - 1 = typical angina; 2 = atypical angina; 3 = non-anginal pain; 4 = asymptomatic
- trestbps: resting blood pressure in mm Hg
- chol: serum cholesterol in mg/dl
- fbs: fasting blood sugar > 120 mg/dl
 - 1 = true; 0 = false
- restecg: resting electrocardiographic results

Heart Disease Example

https://archive.ics.uci.edu/ml/datasets/Heart+Disease https://github.com/sranck/cposc2019/heart.ipynb

- thalach: maximum heart rate achieved
- exang: exercise induced angina
 - 1 = yes; 0 = no
- oldpeak: ST depression induced by exercise relative to rest
- slope: the slope of the peak exercise ST segment
 - 1 = upsloping; 2 = flat; 3 = downsloping
- ca: number of major vessels (0-3) colored by flourosopy
- thal:
 - 3 = normal; 6 = fixed defect; 7 = reversable defect
- num: diagnosis of heart disease (angiographic disease status)
 - 0 = absence; 1, 2, 3, 4 = presence

https://archive.ics.uci.edu/ml/datasets/Heart+Disease https://github.com/sranck/cposc2019/heart.ipynb

```
>>> heart = pd.read_csv('data/processed.cleveland.data', names=names, dtype=dtype, na_values='?')
>>> heart.dropna(inplace=True)
```

	age	sex	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	num
0	63	1	1	145	233	1	2	150	0	2.3	3	0	6	0
1	67	1	4	160	286	0	2	108	1	1.5	2	3	3	2
2	67	1	4	120	229	0	2	129	1	2.6	2	2	7	1
3	37	1	3	130	250	0	0	187	0	3.5	3	0	3	0
4	41	0	2	130	204	0	2	172	0	1.4	1	0	3	0
297	57	0	4	140	241	0	0	123	1	0.2	2	0	7	1
298	45	1	1	110	264	0	0	132	0	1.2	2	0	7	1
299	68	1	4	144	193	1	0	141	0	3.4	2	2	7	2
300	57	1	4	130	131	0	0	115	1	1.2	2	1	7	3
301	57	0	2	130	236	0	2	174	0	0.0	2	1	3	1

297 rows × 14 columns

One Hot Encoding

https://archive.ics.uci.edu/ml/datasets/Heart+Disease https://github.com/sranck/cposc2019/heart.ipynb

>>> heart.cp

>>> pd.get_dummies(heart.cp, prefix='cp')

	cp_1	cp_2	cp_3	ср_4
0	1	0	0	0
1	0	0	0	1
2	0	0	0	1
3	0	0	1	0
4	0	1	0	0
297	0	0	0	1
298	1	0	0	0
299	0	0	0	1
300	0	0	0	1
301	0	1	0	0

297 rows × 4 columns

Training Set / Test Set

https://archive.ics.uci.edu/ml/datasets/Heart+Disease https://github.com/sranck/cposc2019/heart.ipynb

75 rows × 1 columns

y test

>>> x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2)

	age	sex	trestbps	 thal_3	thal_6	thal_7		у
278	57	1	154	 1	0	0	27	8 True
259	57	1	124	 0	0	1	25	9 True
7	57	0	120	 1	0	0		7 False
186	42	1	120	 0	0	1	18	6 False
172	59	0	174	 1	0	0	17	2 True
107	57	1	128	 0	0	1	10	7 True
83	68	1	180	 0	0	1	8	3 True
17	54	1	140	 1	0	0	1	7 False
233	74	0	120	 1	0	0	23	3 False
99	48	1	122	 1	0	0	9	9 False
222 1	OWC >	. 20 .	columns				0.00	

222 rows × 20 columns 222 rows × 1 columns

x_train

259	True
7	False
186	False
172	True
107	True
83	True
17	False
233	False
99	False

y_train

	age	sex	trestbps	 thal_3	thal_6	thal_7			
81	53	0	130	 1	0	0		81	Fals
126	56	0	200	 0	0	1	1	126	Tru
106	59	1	140	 0	0	1	1	106	Tru
279	58	0	130	 1	0	0	2	279	Fals
268	40	1	152	 0	0	1	2	268	Tru
264	61	1	138	 1	0	0	2	264	Tru
153	55	1	160	 0	0	1	1	153	Tru
221	54	0	108	 1	0	0	2	221	Fals
5	56	1	120	 1	0	0		5	Fals
250	57	1	110	 0	1	0	2	250	Fals

x_test

75 rows × 20 columns

Random Forest

https://archive.ics.uci.edu/ml/datasets/Heart+Disease https://github.com/sranck/cposc2019/heart.ipynb

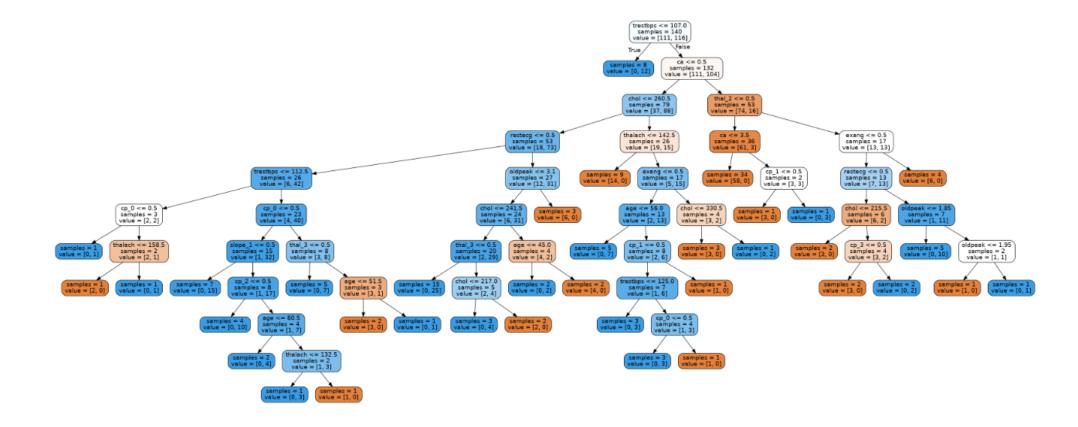
```
>>> rf = RandomForestClassifier(n_estimators=500)
>>> rf.fit(x_train, y_train)
```

	age	sex	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	ca	cp_1	cp_2	ср_3	ср_4	slope_1	slope_2	slope_3	thal_3	thal_6	thal_7
278	57	1	154	232	0	2	164	0	0.0	1	0	1	0	0	1	0	0	1	0	0
259	57	1	124	261	0	0	141	0	0.3	0	0	1	0	0	1	0	0	0	0	1
7	57	0	120	354	0	0	163	1	0.6	0	0	0	0	1	1	0	0	1	0	0
186	42	1	120	240	1	0	194	0	0.8	0	0	0	1	0	0	0	1	0	0	1
172	59	0	174	249	0	0	143	1	0.0	0	0	0	0	1	0	1	0	1	0	0
																				•••
107	57	1	128	229	0	2	150	0	0.4	1	0	0	1	0	0	1	0	0	0	1
83	68	1	180	274	1	2	150	1	1.6	0	0	0	1	0	0	1	0	0	0	1
17	54	1	140	239	0	0	160	0	1.2	0	0	0	0	1	1	0	0	1	0	0
233	74	0	120	269	0	2	121	1	0.2	1	0	1	0	0	1	0	0	1	0	0
99	48	1	122	222	0	2	186	0	0.0	0	0	0	0	1	1	0	0	1	0	0

222 rows × 20 columns

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```
>>> rf = RandomForestClassifier(n_estimators=500)
>>> rf.fit(x_train, y_train)
```



Random Forest

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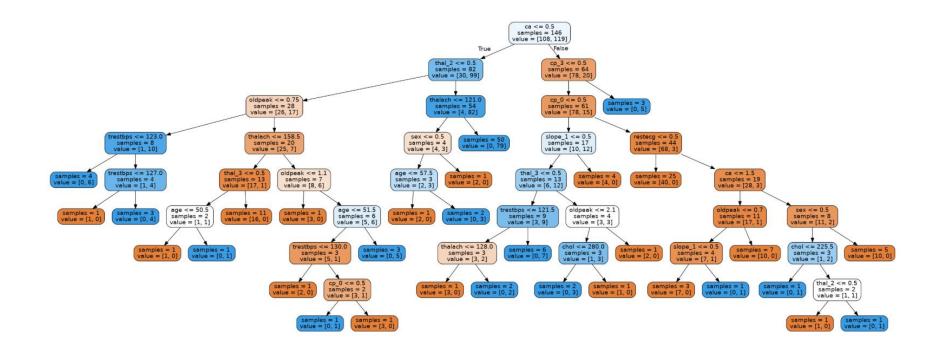
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>>> rf.fit(x_train, y_train)
```

	age	sex	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	ca	cp_1	cp_2	cp_3	ср_4	slope_1	slope_2	slope_3	thal_3	thal_6	thal_7
278	57	1	154	232	0	2	164	0	0.0	1	0	1	0	0	1	0	0	1	0	0
259	57	1	124	261	0	0	141	0	0.3	0	0	1	0	0	1	0	0	0	0	1
7	57	0	120	354	0	0	163	1	0.6	0	0	0	0	1	1	0	0	1	0	0
186	42	1	120	240	1	0	194	0	0.8	0	0	0	1	0	0	0	1	0	0	1
172	59	0	174	249	0	0	143	1	0.0	0	0	0	0	1	0	1	0	1	0	0
107	57	1	128	229	0	2	150	0	0.4	1	0	0	1	0	0	1	0	0	0	1
83	68	1	180	274	1	2	150	1	1.6	0	0	0	1	0	0	1	0	0	0	1
17	54	1	140	239	0	0	160	0	1.2	0	0	0	0	1	1	0	0	1	0	0
233	74	0	120	269	0	2	121	1	0.2	1	0	1	0	0	1	0	0	1	0	0
99	48	1	122	222	0	2	186	0	0.0	0	0	0	0	1	1	0	0	1	0	0

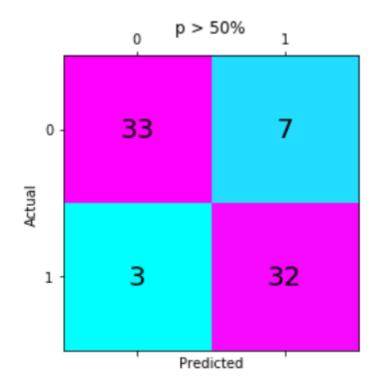
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```
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```

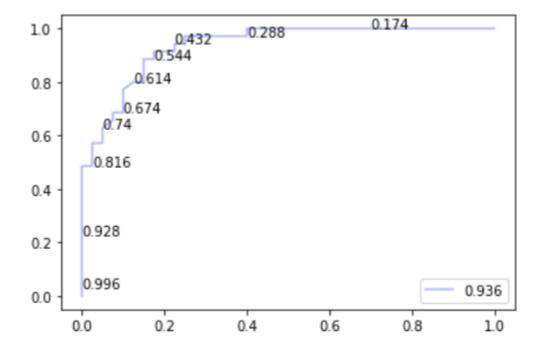


Confusion Matrix



ROC Curve

- Receiver Operating Characteristic
- True Positive Rate (y-axis) vs False Positive Rate (x-axis)

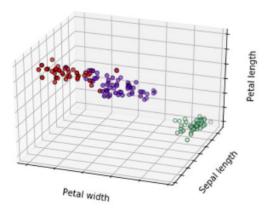


Supervised Learning

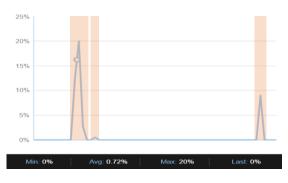
Unsupervised Learning

Unsupervised Learning

- Find patterns in unlabeled data
- Clustering
 - Arrange objects into groups
- Anomaly detection
 - Identify rare events / outliers



Clustering

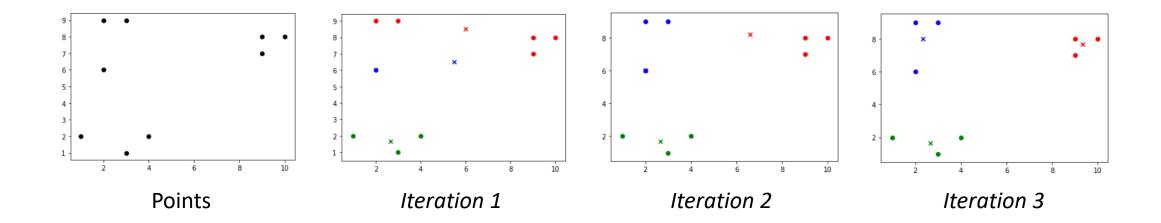


Anomaly detection

https://voteview.com/data https://github.com/sranck/cposc2019/senate.ipynb

- Voteview
 - https://voteview.com/data
 - https://voteview.com/static/data/out/votes/S114 votes.csv
 - https://voteview.com/static/data/out/members/S114 members.csv
- Voting record for the 114th Congress (Senate only)
 - 100 senators
 - 502 votes
 - 50,200 voting records
- What happens if we cluster senators by their voting record?

Groups n points into k clusters



Data Frame

https://github.com/sranck/cposc2019/senate.ipynb

	congress	cnamber	rollnumber	icpsr	cast_code	prop
0	114	Senate	1	14009	6	100.0
1	114	Senate	1	14226	6	100.0
2	114	Senate	1	14307	1	90.5
3	114	Senate	1	14435	1	99.8
4	114	Senate	1	14440	1	91.1
50195	114	Senate	502	49308	6	34.1
50196	114	Senate	502	49700	6	8.9
50197	114	Senate	502	49703	1	69.3
50198	114	Senate	502	49706	1	91.8
50199	114	Senate	502	94659	6	4.5

50200 rows × 6 columns

congress chamber rollnumber ioner cast code prob

	senator_id	vote_id	vote_cast
0	14009	1	6
1	14226	1	6
2	14307	1	1
3	14435	1	1
4	14440	1	1
50195	49308	502	6
50196	49700	502	6
50197	49703	502	1
50198	49706	502	1
50199	94659	502	6

50200 rows × 3 columns

Co-occurrence Matrix

```
>>> votes.set_index(['vote_id', 'vote_cast'], inplace=True)
>>> senator_pairs = votes.join(votes, lsuffix='_a', rsuffix='_b')
>>> senator_pairs = senator_pairs.groupby(['senator_id_a', 'senator_id_b']).n.count()
>>> matrix = senator_pairs.pivot(index='senator_id_a', columns='senator_id_b')
```

0 14009 1 6 1 14226 1 6 2 14307 1 1 3 14435 1 1 4 14440 1 1 50195 49308 502 6 50196 49700 502 6 50197 49703 502 1 50198 49706 502 1 50199 94659 502 6		senator_id	vote_id	vote_cast
2 14307 1 1 3 14435 1 1 4 14440 1 1 50195 49308 502 6 50196 49700 502 6 50197 49703 502 1 50198 49706 502 1	0	14009	1	6
3 14435 1 1 4 14440 1 1 50195 49308 502 6 50196 49700 502 6 50197 49703 502 1 50198 49706 502 1	1	14226	1	6
4 14440 1 1 1	2	14307	1	1
	3	14435	1	1
50195 49308 502 6 50196 49700 502 6 50197 49703 502 1 50198 49706 502 1	4	14440	1	1
50196 49700 502 6 50197 49703 502 1 50198 49706 502 1				
50197 49703 502 1 50198 49706 502 1	50195	49308	502	6
50198 49706 502 1	50196	49700	502	6
	50197	49703	502	1
50199 94659 502 6	50198	49706	502	1
	50199	94659	502	6

50200 rows × 3 columns

senator id vote id vote cast



senator_id	b 14009	14226	14307	14435	14440	•••	49308	49700	49703	49706	94659
senator_id	_a										
1400	9 502	434	206	181	213		226	408	396	418	394
1422	26 434	502	181	168	189		207	417	378	432	417
1430	07 206	181	502	461	446		454	154	296	176	143
1443	35 181	168	461	502	431		447	141	272	160	138
1444	10 213	189	446	431	502		430	158	296	181	161
4930	08 226	207	454	447	430		502	159	299	195	156
4970	00 408	417	154	141	158		159	502	339	414	439
4970	396	378	296	272	296		299	339	502	353	335
4970	06 418	432	176	160	181		195	414	353	502	402
946	59 394	417	143	138	161		156	439	335	402	502

100 rows × 100 columns

K-means Clustering

https://voteview.com/data
https://github.com/sranck/cposc2019/senate.ipynb

```
>>> km = KMeans(n_clusters=2).fit(matrix)
>>> clusters = pd.DataFrame({ 'cluster': km.labels_ }, matrix.index.rename('senator_id'))
```

name	party	
		senator_id
LEAHY, Patrick Joseph	D	14307
MARKEY, Edward John	D	14435
MIKULSKI, Barbara Ann	D	14440
NELSON, Clarence William (Bill)	D	14651
SCHUMER, Charles Ellis (Chuck)	D	14858
HEITKAMP, Mary Kathryn (Heidi)	D	41303
KAINE, Timothy Michael (Tim)	D	41305
BOOKER, Cory Anthony	D	41308
FEINSTEIN, Dianne	D	49300
MURRAY, Patty	D	49308

46 rows × 2 columns

name	party	
		senator_id
COCHRAN, William Thad	R	14009
GRASSLEY, Charles Ernest	R	14226
HATCH, Orrin Grant	R	14503
COATS, Daniel Ray	R	14806
ROBERTS, Charles Patrick (Pat)	R	14852
ROUNDS, Marion Michael (Mike)	R	41505
SESSIONS, Jefferson Beauregard III (Jeff)	R	49700
COLLINS, Susan Margaret	R	49703
ENZI, Michael B.	R	49706
SHELBY, Richard C.	R	94659

54 rows × 2 columns

```
>>> senators[clusters.cluster == 0]
```

>>> senators[clusters.cluster == 1]

Confusion Matrix

