

Kecerdasan Bisnis Terapan

Prescriptive Analytics

Optimization and Simulation

Husni

Lab. Riset JTIF UTM

Business Intelligence (BI)

1 Introduction to BI and Data Science

2 Descriptive Analytics

3 Predictive Analytics

④ Prescriptive Analytics

5 Big Data Analytics

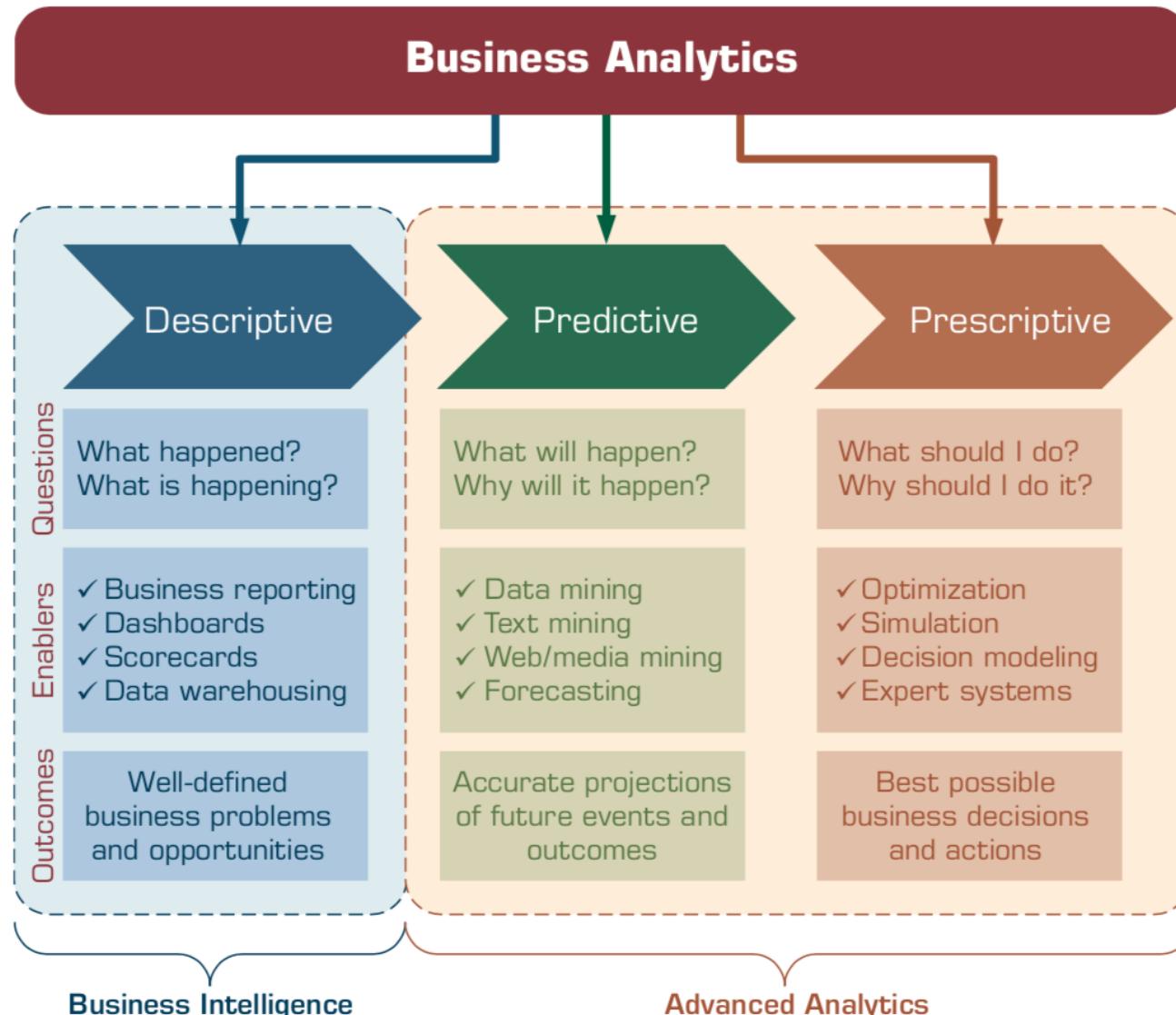
6 Future Trends

Prescriptive Analytics: Optimization and Simulation

Outline

- Prescriptive Analytics
- Model-Based Decision Making
- Structure of Mathematical Models for Decision Support
- Certainty, Uncertainty, and Risk
- Mathematical Programming Optimization
- Simulation

Business Analytics and Prescriptive Analytics



Prescriptive Analytics Model Examples

- **Modeling** is a key element for prescriptive analytics.
- Employ a **mathematical model** to be able to recommend a decision for any realistic problem.
- Building a **probability-based response maximization model** with the budget as a constraint would give us the information we are seeking.

Identification of the Problem and Environmental Analysis

- Environmental scanning and analysis
 - Monitoring, scanning, and interpretation of collected information
- Business intelligence/business analytics (BI/BA) tools can help identify problems by scanning for them.
- Variable Identification
- Forecasting (Predictive Analytics)

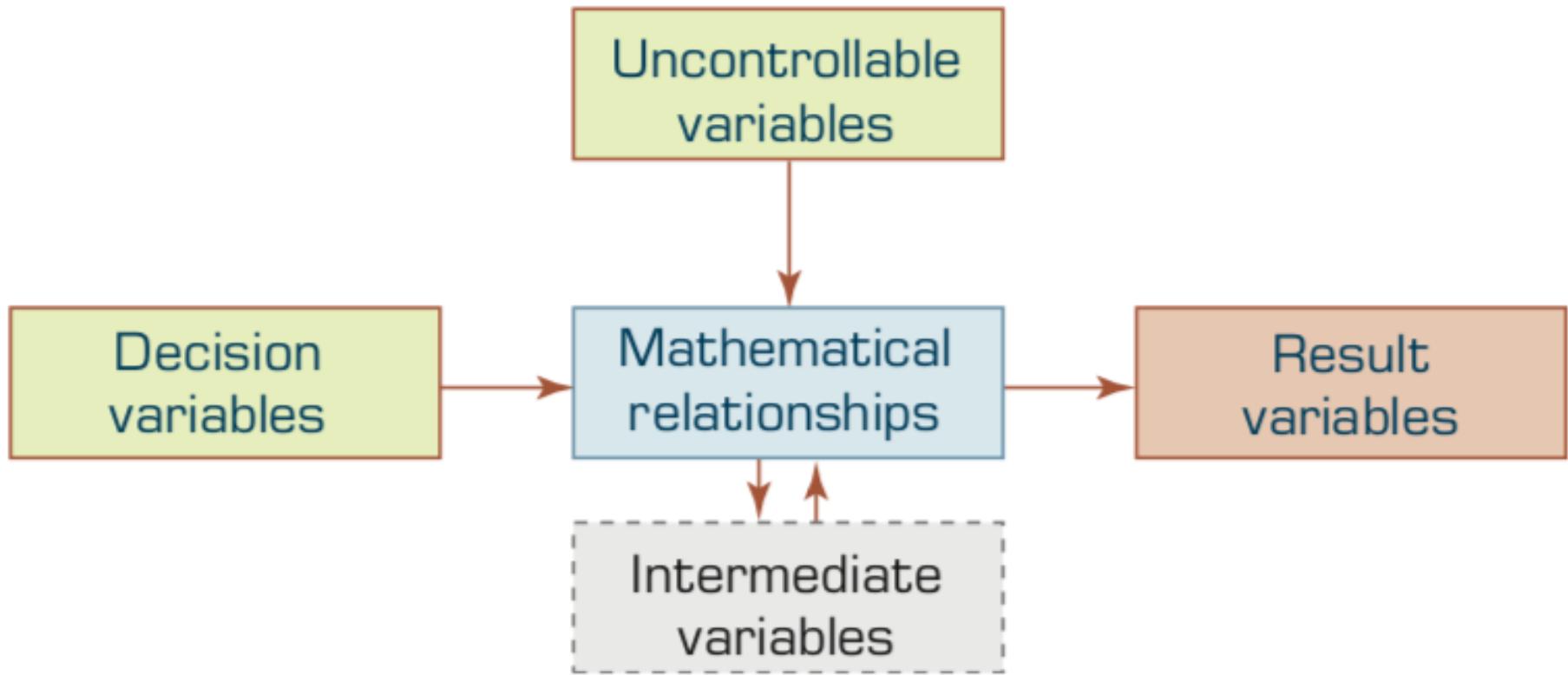
Categories of Models

Category	Process and Objective	Representative Techniques
Optimization of problems with few alternatives	Find the best solution from a small number of alternatives	Decision tables, decision trees, analytic hierarchy process
Optimization via algorithm	Find the best solution from a large number of alternatives, using a step-by-step improvement process	Linear and other mathematical programming models, network models
Optimization via an analytic formula	Find the best solution in one step, using a formula	Some inventory models
Simulation	Find a good enough solution or the best among the alternatives checked, using experimentation	Several types of simulation
Heuristics	Find a good enough solution, using rules	Heuristic programming, expert systems
Predictive models	Predict the future for a given scenario	Forecasting models, Markov analysis
Other models	Solve a what-if case, using a formula	Financial modeling, waiting lines

Structure of Mathematical Models for Decision Support

- The Components of Decision Support Mathematical Models
- The Structure of Mathematical Models

The General Structure of a Quantitative Model



Examples of Components of Models

Area	Decision Variables	Result Variables	Uncontrollable Variables and Parameters
Financial investment	Investment alternatives and amounts	Total profit, risk Rate of return on investment (ROI) Earnings per share Liquidity level	Inflation rate Prime rate Competition
Marketing	Advertising budget Where to advertise	Market share Customer satisfaction	Customer's income Competitor's actions
Manufacturing	What and how much to produce Inventory levels Compensation programs	Total cost Quality level Employee satisfaction	Machine capacity Technology Materials prices
Accounting	Use of computers Audit schedule	Data processing cost Error rate	Computer technology Tax rates Legal requirements
Transportation	Shipments schedule Use of smart cards	Total transport cost Payment float time	Delivery distance Regulations
Services	Staffing levels	Customer satisfaction	Demand for services

The Structure of Mathematical Models

A very simple financial model is

$$P = R - C$$

where P = profit, R = revenue, and C = cost.

The Structure of Mathematical Models

Financial model (present-value cash flow model)

$$P = F / (1 + i)^n$$

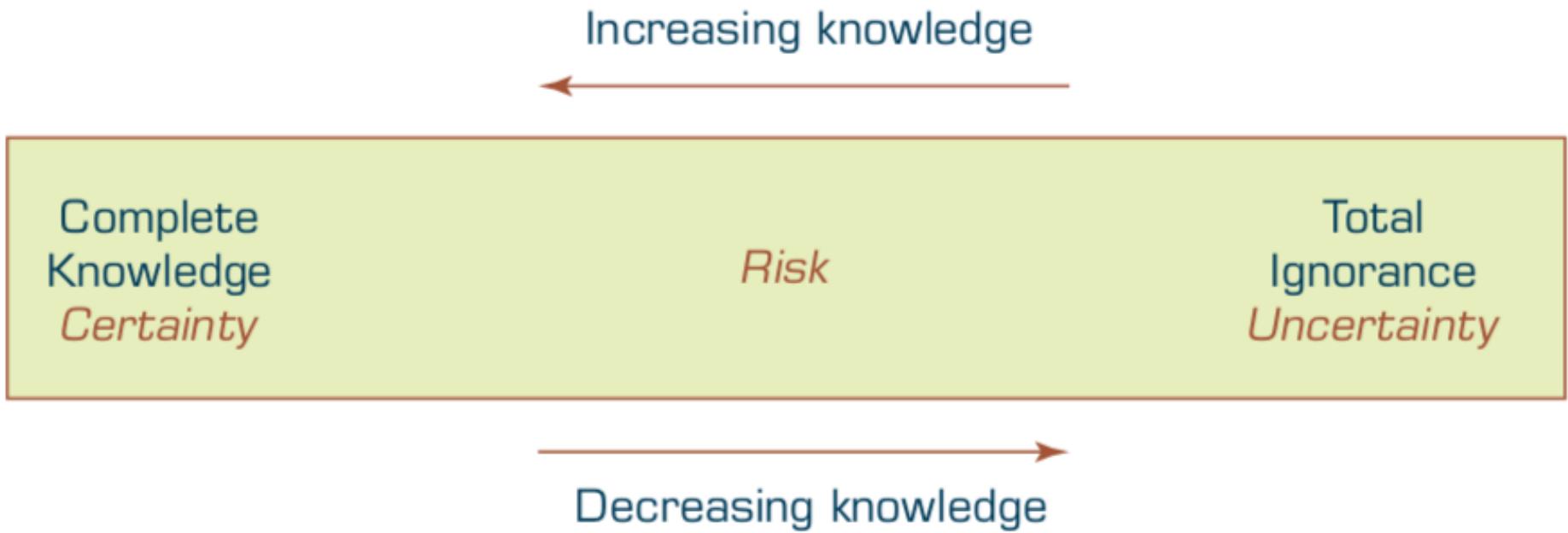
where P = present value, F = a future single payment in dollars, i = interest rate (percentage), and n = number of years.

$$P = 100,000 / (1 + 0.1)^5 = 62,092$$

Certainty, Uncertainty, and Risk

- Decision Making under Certainty
- Decision Making under Uncertainty
- Decision Making under Risk (Risk Analysis)

The Zones of Decision Making

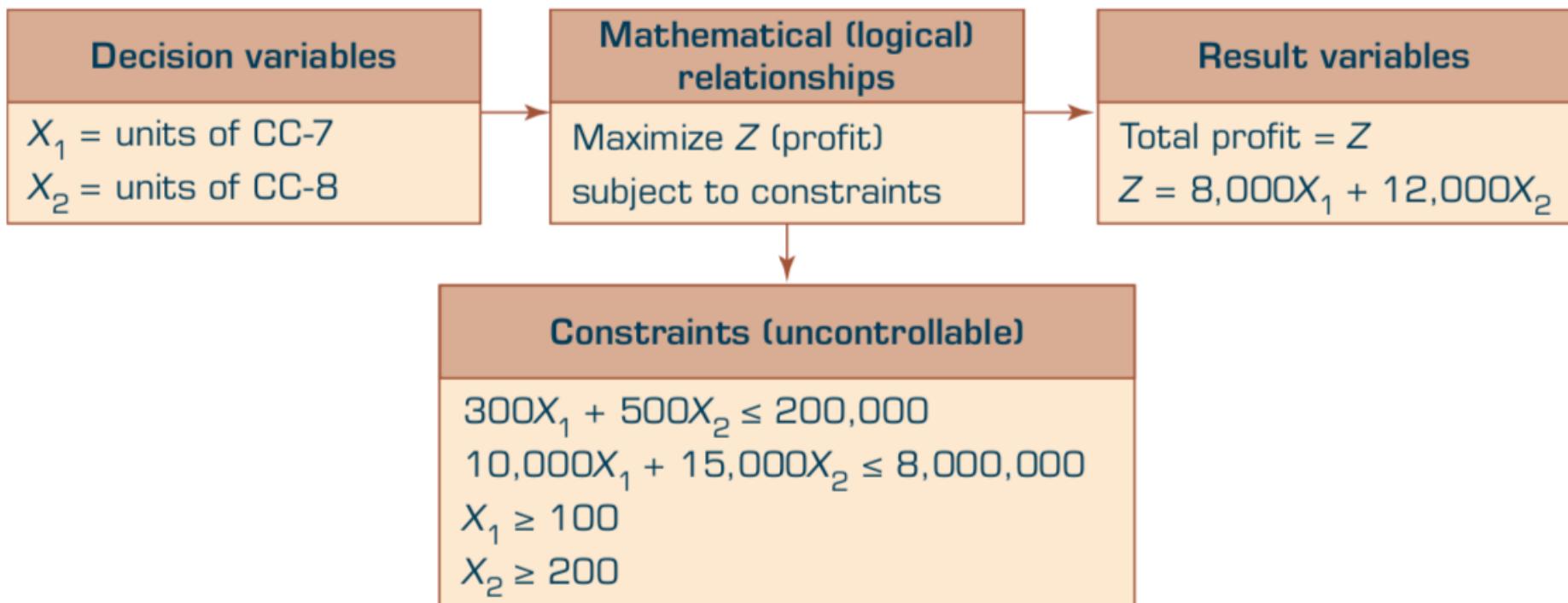


Mathematical Programming

Optimization

- **Mathematical programming**
 - a family of tools designed to help **solve managerial problems** in which the decision maker must **allocate scarce resources** among **competing activities** to **optimize a measurable goal**.
- **Linear programming (LP)** is the best-known technique in a family of optimization tools called *mathematical programming*.

Mathematical Model of a Product-Mix Example



Prescriptive Analytics, Operations research/ Management Science

- Multiple Goals
- Sensitivity Analysis
- What-If Analysis
- Goal Seeking

Decision Analysis with Decision Tables and Decision Trees

- **Decision tables**
 - conveniently organize information and knowledge in a systematic, tabular manner to prepare it for analysis.
- **Decision tree**
 - shows the relationships of the problem graphically and can handle complex situations in a compact form.

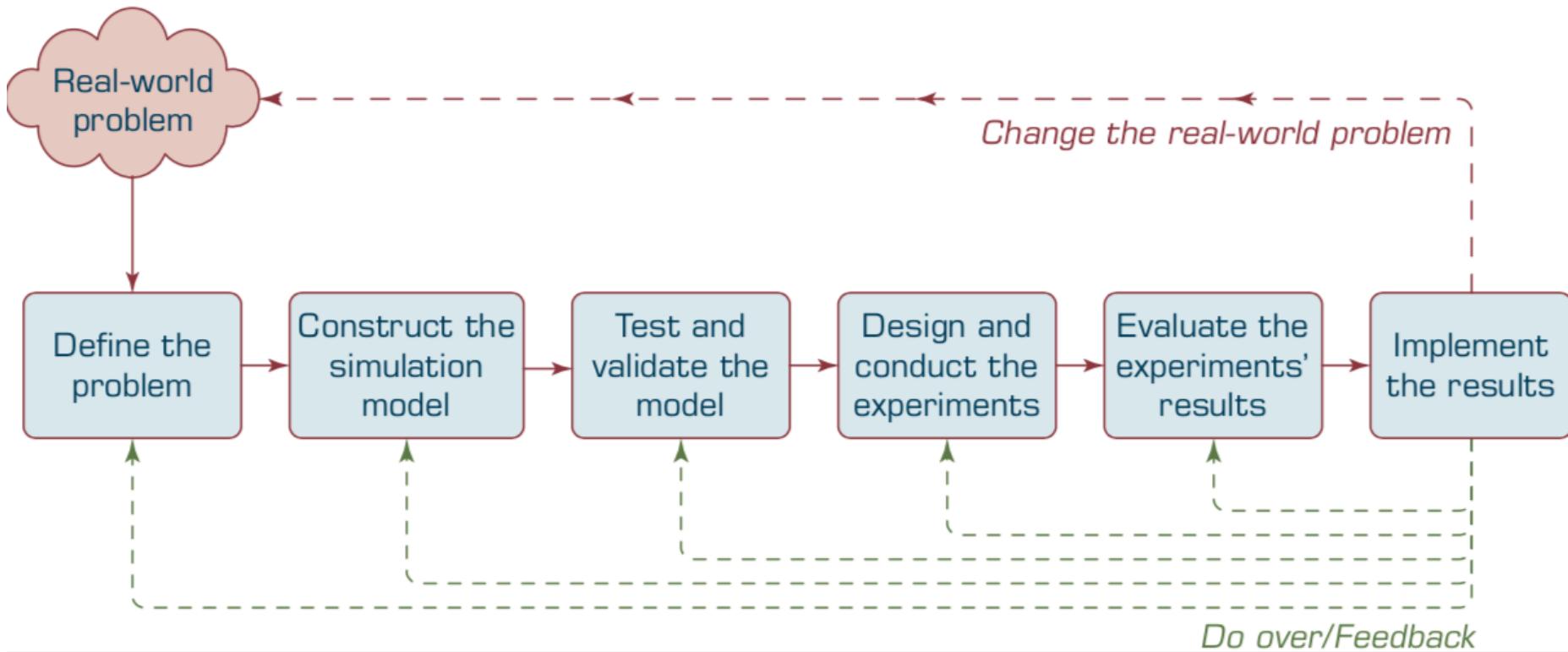
Investment Problem Decision Table Model

State of Nature (Uncontrollable Variables)			
Alternative	Solid Growth (%)	Stagnation (%)	Inflation (%)
Bonds	12.0	6.0	3.0
Stocks	15.0	3.0	-2.0
CDs	6.5	6.5	6.5

Multiple Goals

Alternative	Yield (%)	Safety	Liquidity
Bonds	8.4	High	High
Stocks	8.0	Low	High
CDs	6.5	Very high	High

The Process of Simulation



Discrete versus Continuous Probability Distributions

Daily Demand	Discrete Probability	Continuous Probability
5	0.10	Daily demand is normally distributed with a mean of 7 and a standard deviation of 1.2
6	0.15	
7	0.30	
8	0.25	
9	0.20	

Simulation Types

- Monte Carlo Simulation
- Discrete Event Simulation

Visual Interactive Simulation

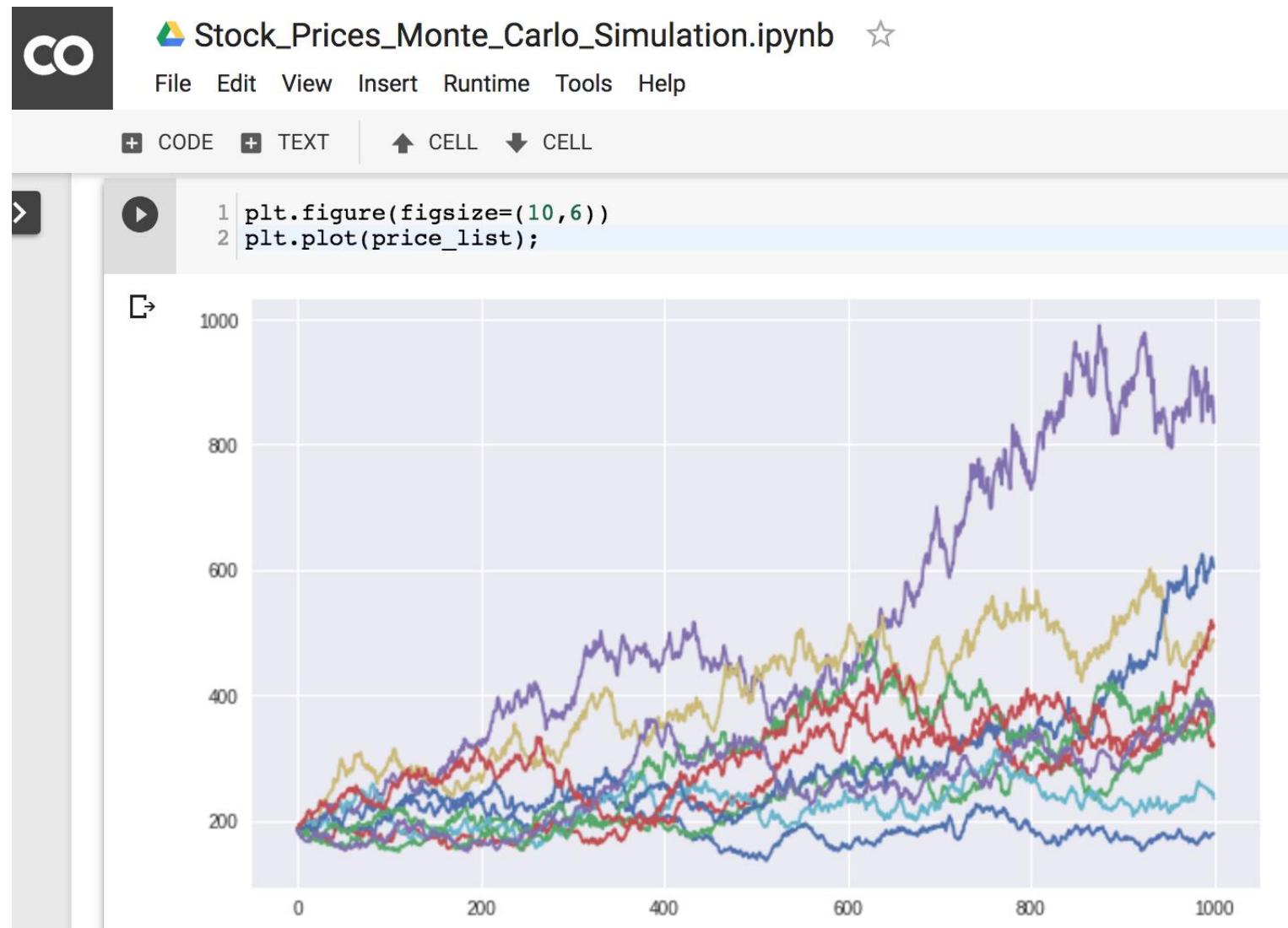
- Conventional Simulation Inadequacies
- Visual Interactive Simulation (VIS)
 - Visual Interactive Modeling (VIM)
- Visual Interactive Models and DSS

Simulation Software

- Analytica
(Lumina Decision Systems, lumina.com)
- Excel add-ins Crystal Ball
- @RISK (Palisade Corp., palisade.com)
- Arena
- Simio (simio.com)
- ExtendSim (extendsim.com)
- SAS JMP

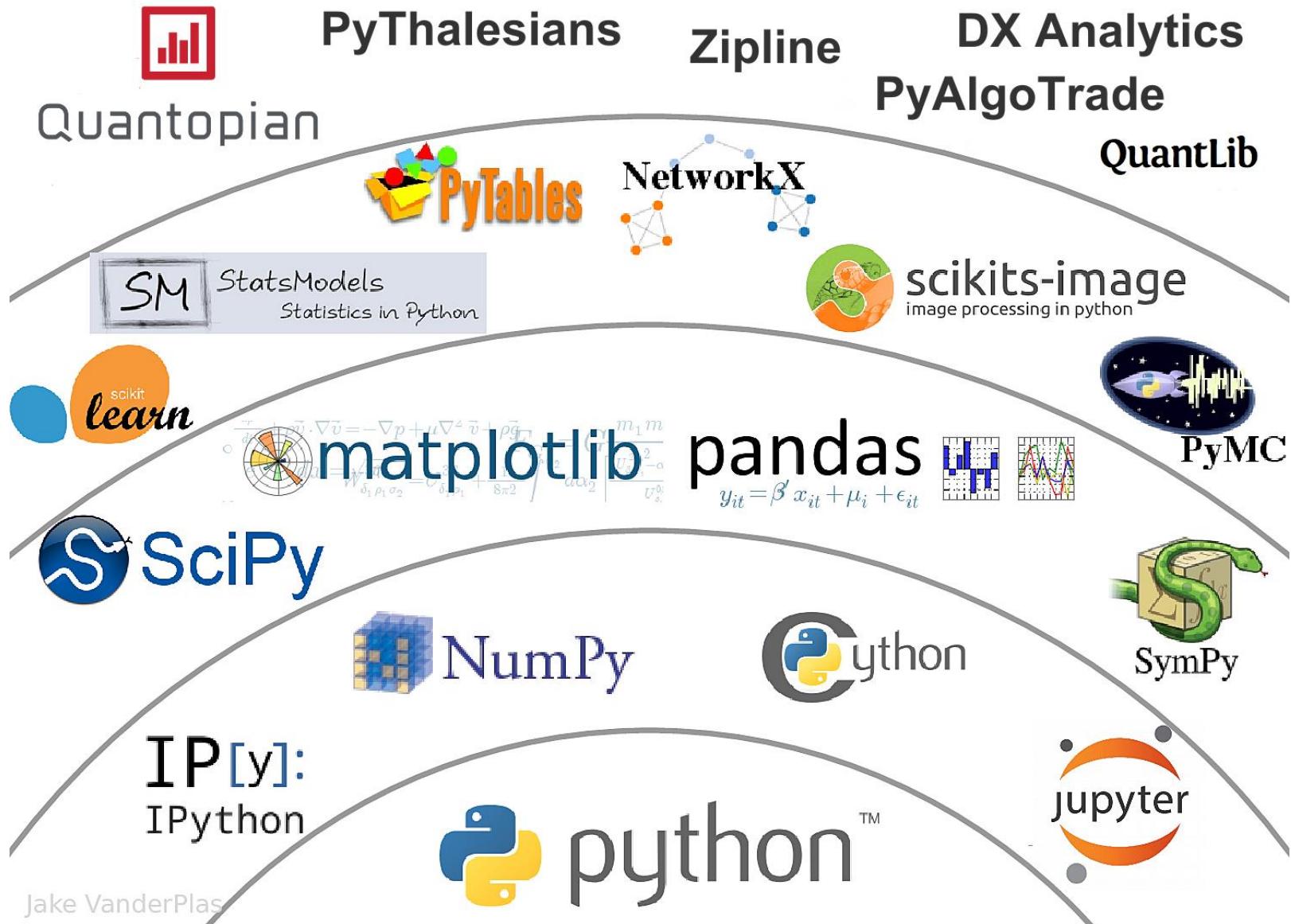
Monte Carlo Simulation

Monte Carlo Simulation to Forecast Stock Prices



Python Pandas for Finance

The Quant Finance PyData Stack



AAPL



Python in Google Colab

<https://colab.research.google.com/drive/1FEG6DnGvrfUbeo4zJ1zTunjMqf2RkCrT>

CO python101.ipynb ★

File Edit View Insert Runtime Tools Help

CODE TEXT CELL CELL COMMENT SHARE A

```
1 # !pip install pandas_datareader
2 import pandas as pd
3 import pandas_datareader.data as web
4 import matplotlib.pyplot as plt
5 import seaborn as sns
6 import datetime as dt
7 %matplotlib inline
8
9 #Read Stock Data from Yahoo Finance
10 end = dt.datetime.now()
11 #start = dt.datetime(end.year-2, end.month, end.day)
12 start = dt.datetime(2016, 1, 1)
13 df = web.DataReader("AAPL", 'yahoo', start, end)
14 df.to_csv('AAPL.csv')
15 df.from_csv('AAPL.csv')
16 df.tail()
17
18 df['Adj Close'].plot(legend=True, figsize=(12, 8), title='AAPL', label='Adj Close')
19 plt.figure(figsize=(12,9))
20 top = plt.subplot2grid((12,9), (0, 0), rowspan=10, colspan=9)
21 bottom = plt.subplot2grid((12,9), (10,0), rowspan=2, colspan=9)
22 top.plot(df.index, df['Adj Close'], color='blue') #df.index gives the dates
23 bottom.bar(df.index, df['Volume'])
24
25 # set the labels
26 top.axes.get_xaxis().set_visible(False)
27 top.set_title('AAPL')
28 top.set_ylabel('Adj Close')
29 bottom.set_ylabel('Volume')
30
31 plt.figure(figsize=(12,9))
32 sns.distplot(df['Adj Close'].dropna(), bins=50, color='purple')
33
34 # simple moving averages
35 df['MA05'] = df['Adj Close'].rolling(5).mean() #5 days
36 df['MA20'] = df['Adj Close'].rolling(20).mean() #20 days
37 df['MA60'] = df['Adj Close'].rolling(60).mean() #60 days
38 df2 = pd.DataFrame({'Adj Close': df['Adj Close'], 'MA05': df['MA05'], 'MA20': df['MA20'], 'MA60': df['MA60']})
39 df2.plot(figsize=(12, 9), legend=True, title='AAPL')
40 df2.to_csv('AAPL_MA.csv')
41 fig = plt.gcf()
42 fig.set_size_inches(12, 9)
43 fig.savefig('AAPL_plot.png', dpi=300)
```

! pip install pandas_datareader

```
1 | ! pip install pandas_datareader

Collecting pandas_datareader
  Downloading https://files.pythonhosted.org/packages/cc/5c/ea5b6dcfd0f55c5fb1e37fb45335ec01cceca199b8a79339137f5ed269e0/pandas_datarea
  100% |██████████| 112kB 2.7MB/s
Collecting lxml (from pandas_datareader)
  Downloading https://files.pythonhosted.org/packages/03/a4/9eea8035fc7c7670e5eab97f34ff2ef0ddd78a491bf96df5accedb0e63f5/lxml-4.2.5-cp3
  100% |██████████| 5.8MB 7.5MB/s
Requirement already satisfied: pandas>=0.19.2 in /usr/local/lib/python3.6/dist-packages (from pandas_datareader) (0.22.0)
Requirement already satisfied: requests>=2.3.0 in /usr/local/lib/python3.6/dist-packages (from pandas_datareader) (2.18.4)
Requirement already satisfied: wrapt in /usr/local/lib/python3.6/dist-packages (from pandas_datareader) (1.10.11)
Requirement already satisfied: python-dateutil>=2 in /usr/local/lib/python3.6/dist-packages (from pandas>=0.19.2->pandas_datareader) (2
Requirement already satisfied: numpy>=1.9.0 in /usr/local/lib/python3.6/dist-packages (from pandas>=0.19.2->pandas_datareader) (1.14.6)
Requirement already satisfied: pytz>=2011k in /usr/local/lib/python3.6/dist-packages (from pandas>=0.19.2->pandas_datareader) (2018.5)
Requirement already satisfied: idna<2.7,>=2.5 in /usr/local/lib/python3.6/dist-packages (from requests>=2.3.0->pandas_datareader) (2.6)
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in /usr/local/lib/python3.6/dist-packages (from requests>=2.3.0->pandas_datareader)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.6/dist-packages (from requests>=2.3.0->pandas_datareader) (
Requirement already satisfied: urllib3<1.23,>=1.21.1 in /usr/local/lib/python3.6/dist-packages (from requests>=2.3.0->pandas_datareader)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dist-packages (from python-dateutil>=2->pandas>=0.19.2->pandas_data
Installing collected packages: lxml, pandas-datareader
Successfully installed lxml-4.2.5 pandas-datareader-0.7.0
```

conda install pandas-datareader

```
iMyday—bash—80x24
[iMyday-MacBook-Pro:~ imyday$ conda install pandas-datareader
Fetching package metadata .....
Solving package specifications: .

Package plan for installation in environment /Users/imyday/anaconda:

The following NEW packages will be INSTALLED:

pandas-datareader: 0.2.1-py36_0
requests-file:    1.4.1-py36_0

Proceed ([y]/n)? y

requests-file- 100% |#####
pandas-datarea 100% |#####
[iMyday-MacBook-Pro:~ imyday$ conda list
# packages in environment at /Users/imyday/anaconda:
#
_license          1.1                  py36_1
alabaster         0.7.9                py36_0
anaconda          4.3.1                np111py36_0
anaconda-client   1.6.0                py36_0
anaconda-navigator 1.5.0                py36_0
anaconda-project  0.4.1                py36_0
```

AAPL



Finance Data from Yahoo Finance

```
# !pip install pandas_datareader
import pandas_datareader.data as web
import datetime as dt
#Read Stock Data from Yahoo Finance
end = dt.datetime(2017, 12, 31)
start = dt.datetime(2016, 1, 1)
df = web.DataReader("AAPL", 'yahoo', start, end)
df.to_csv('AAPL.csv')
df.from_csv('AAPL.csv')
df.tail()
```

```
# !pip install pandas_datareader
import pandas as pd
import pandas_datareader.data as web
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
%matplotlib inline

#Read Stock Data from Yahoo Finance
end = dt.datetime.now()
#start = dt.datetime(end.year-2, end.month,
end.day)
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```
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```



```
plt.figure(figsize=(12, 9))
top = plt.subplot2grid((12, 9), (0, 0),
rowspan=10, colspan=9)
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top.plot(df.index, df['Adj Close'],
color='blue') #df.index gives the dates
bottom.bar(df.index, df['Volume'])
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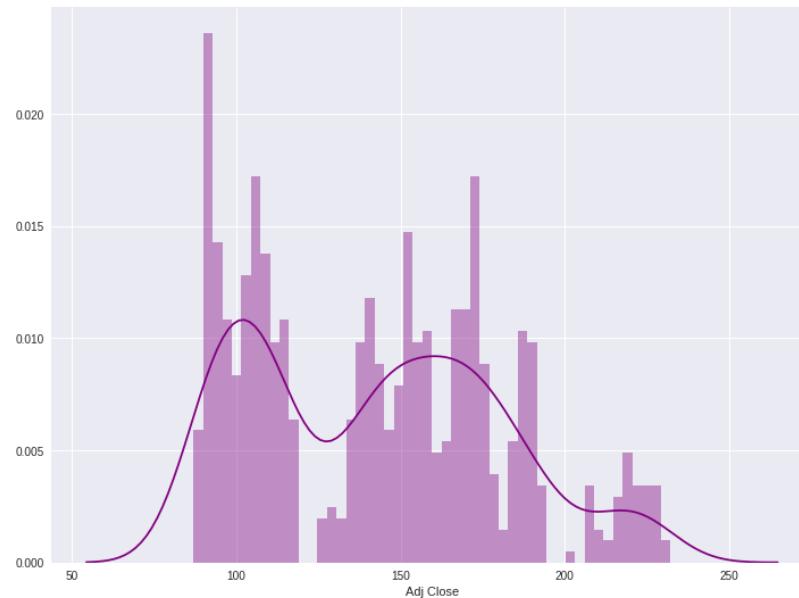


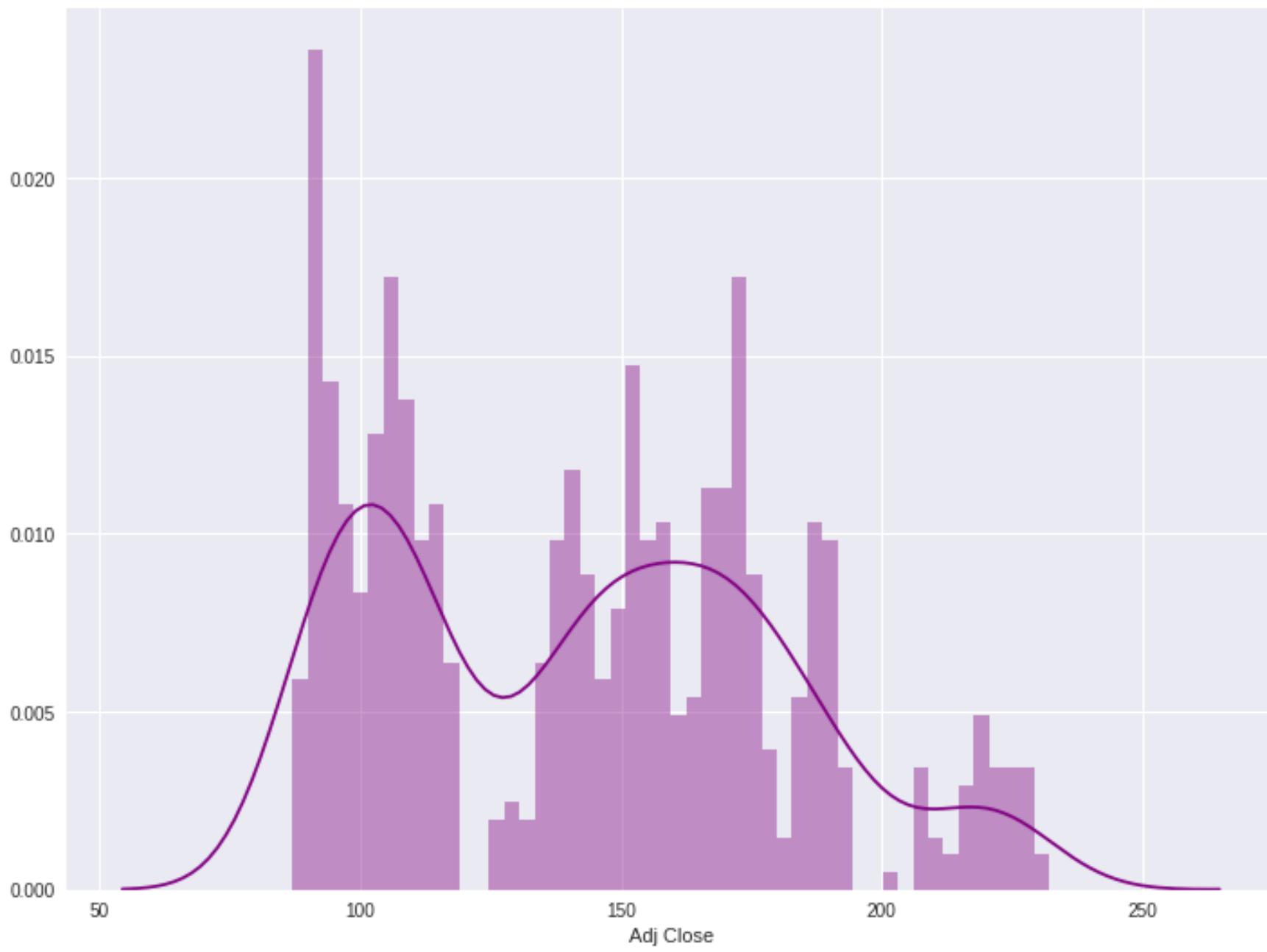
AAPL



```
# set the labels
top.axes.get_xaxis().set_visible(False)
top.set_title('AAPL')
top.set_ylabel('Adj Close')
bottom.set_ylabel('Volume')

plt.figure(figsize=(12, 9))
sns.distplot(df['Adj Close'].dropna(),
bins=50, color='purple')
```





```
# simple moving averages
df['MA05'] = df['Adj Close'].rolling(5).mean()
#5 days
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Close'].rolling(20).mean() #20 days
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Close'].rolling(60).mean() #60 days
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Close'], 'MA05': df['MA05'], 'MA20': df['MA20'],
'MA60': df['MA60']})
df2.plot(figsize=(12, 9), legend=True,
title='AAPL')
df2.to_csv('AAPL_MA.csv')
fig = plt.gcf()
fig.set_size_inches(12, 9)
fig.savefig('AAPL_plot.png', dpi=300)
plt.show()
```

AAPL



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40 df2.to_csv('AAPL_MA.csv')
41 fig = plt.gcf()
42 fig.set_size_inches(12, 9)
43 fig.savefig('AAPL_plot.png', dpi=300)
44 plt.show()

```

Finance Data from Quandl

```
# ! pip install quandl
import quandl
# quandl.ApiConfig.api_key = "YOURAPIKEY"
df = quandl.get("WIKI/AAPL", start_date="2016-01-01", end_date="2017-12-31")
df.to_csv('AAPL.csv')
df.from_csv('AAPL.csv')
df.tail()
```

```
1 # ! pip install quandl
2 import quandl
3 # quandl.ApiConfig.api_key = "YOURAPIKEY"
4 df = quandl.get("WIKI/AAPL", start_date="2016-01-01", end_date="2017-12-31")
5 df.to_csv('AAPL.csv')
6 df.from_csv('AAPL.csv')
7 df.tail()
```

/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:5: FutureWarning: from_csv is deprecated. Please use read_csv(...) instead
"""

Date	Open	High	Low	Close	Volume	Ex-Dividend	Split Ratio	Adj. Open	Adj. High	Adj. Low	Adj. Close	Adj. Volume
2017-12-22	174.68	175.424	174.500	175.01	16052615.0	0.0	1.0	174.68	175.424	174.500	175.01	16052615.0
2017-12-26	170.80	171.470	169.679	170.57	32968167.0	0.0	1.0	170.80	171.470	169.679	170.57	32968167.0
2017-12-27	170.10	170.780	169.710	170.60	21672062.0	0.0	1.0	170.10	170.780	169.710	170.60	21672062.0
2017-12-28	171.00	171.850	170.480	171.08	15997739.0	0.0	1.0	171.00	171.850	170.480	171.08	15997739.0
2017-12-29	170.52	170.590	169.220	169.23	25643711.0	0.0	1.0	170.52	170.590	169.220	169.23	25643711.0

Yahoo Finance Symbols: AAPL Apple Inc. (AAPL)

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YAHOO!
FINANCE

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Finance Home Originals Events Personal Finance Technology Markets Industries NEW My Screeners My Portfolio

S&P 500 2,340.02 -29.45 (-1.24%) 

Dow 30 20,668.01 -237.85 (-1.14%) 

Nasdaq 5,793.83 -107.70 (-1.83%) 

Crude Oil 47.50 +0.16 (+0.34%) 

Gold 1,245.40 -1.10 (-0.09%) 

Quote Lookup

Search for symbols or companies: YHOO, GOOG, DIS

Symbols similar to 'aapl' All Markets ▾

All (9) Stocks (6) Mutual Funds (0) ETFs (1) Indices (2) Futures (0) Currencies (0)

Symbol	Company Name	Last Price	Industry / Category	Type	Exchange
AAPL	Apple Inc.	139.84	Electronic Equipment	Stocks	NMS
AAPL.SW	Apple Inc.	140.70	N/A	Stocks	EBS
AAPL.MX	Apple Inc.	2678.68	Electronic Equipment	Stocks	MEX
AAPL34.FSA	Apple Inc.	0.00	N/A	Stocks	SAO
AAPL34.SA	Apple Inc.	43.14	Electronic Equipment	Stocks	SAO

<http://finance.yahoo.com/q?s=AAPL>

Dow Jones Industrial Average (^DJI)

YAHOO! FINANCE | Go to Quote Summary Page ★

S&P 500
2,344.02
-29.45 (-1.24%)

Dow 30
20,668.01
-237.85 (-1.14%)

Nasdaq
5,793.83
-107.70 (-1.83%)

Crude Oil
47.50
+0.16 (+0.34%)

Gold
1,244.90
-1.60 (-0.13%)

Dow Jones Industrial Average (^DJI) 20,668.01 -237.85 (-1.14%) As of 4:36PM EDT. Market closed.



<http://finance.yahoo.com/chart/^DJI>

TSEC weighted index (^TWII) - Taiwan



Yahoo Finance Charts

TSMC (2330.TW)



Taiwan Semiconductor Manufacturing Company Limited (2330.TW) 192.00 -3.00 (-1.54%)

As of 10:29AM CST. Taiwan Delayed Price. Market open.



```

import pandas as pd
import pandas_datareader.data as web
df = web.DataReader('AAPL', data_source='yahoo',
start='1/1/2010', end='3/21/2017')
df.to_csv('AAPL.csv')
df.tail()

```

```

import pandas as pd
import pandas_datareader.data as web
#df = web.DataReader('AAPL', 'yahoo')
df = web.DataReader('AAPL', data_source='yahoo', start='1/1/2010', end='3/21/2017')
#df = web.DataReader('AAPL', data_source='google', start='1/1/2010', end='3/21/2017')
df.to_csv('AAPL.csv')
df.tail()

```

	Open	High	Low	Close	Volume	Adj Close
Date						
2017-03-15	139.410004	140.750000	139.029999	140.460007	25566800	140.460007
2017-03-16	140.720001	141.020004	140.259995	140.690002	19132500	140.690002
2017-03-17	141.000000	141.000000	139.889999	139.990005	43597400	139.990005
2017-03-20	140.399994	141.500000	140.229996	141.460007	20213100	141.460007
2017-03-21	142.110001	142.800003	139.729996	139.839996	39116800	139.839996

```

df = web.DataReader('GOOG',
data_source='yahoo', start='1/1/1980',
end='3/21/2017')
df.head(10)

```

```

df = web.DataReader('GOOG', data_source='yahoo', start='1/1/1980', end='3/21/2017')
df.head(10)

```

	Open	High	Low	Close	Volume	Adj Close
Date						
2004-08-19	100.000168	104.060182	95.960165	100.340176	44871300	50.119968
2004-08-20	101.010175	109.080187	100.500174	108.310183	22942800	54.100990
2004-08-23	110.750191	113.480193	109.050183	109.400185	18342800	54.645447
2004-08-24	111.240189	111.600192	103.570177	104.870176	15319700	52.382705
2004-08-25	104.960181	108.000187	103.880180	106.000184	9232100	52.947145
2004-08-26	104.950180	107.950188	104.660179	107.910182	7128600	53.901190
2004-08-27	108.100185	108.620186	105.690180	106.150181	6241200	53.022069
2004-08-30	105.280178	105.490184	102.010172	102.010172	5221400	50.954132
2004-08-31	102.300173	103.710180	102.160177	102.370175	4941200	51.133953
2004-09-01	102.700174	102.970180	99.670169	100.250171	9181600	50.075011

df.tail(10)

```
df.tail(10)
```

	Open	High	Low	Close	Volume	Adj Close
Date						
2017-03-08	833.510010	838.150024	831.789978	835.369995	988700	835.369995
2017-03-09	836.000000	842.000000	834.210022	838.679993	1259900	838.679993
2017-03-10	843.280029	844.909973	839.500000	843.250000	1701100	843.250000
2017-03-13	844.000000	848.684998	843.250000	845.539978	1149500	845.539978
2017-03-14	843.640015	847.239990	840.799988	845.619995	779900	845.619995
2017-03-15	847.590027	848.630005	840.770020	847.200012	1379600	847.200012
2017-03-16	849.030029	850.849976	846.130005	848.780029	970400	848.780029
2017-03-17	851.609985	853.400024	847.109985	852.119995	1712300	852.119995
2017-03-20	850.010010	850.219971	845.150024	848.400024	1190300	848.400024
2017-03-21	851.400024	853.500000	829.020020	830.460022	2442900	830.460022

df.count()

```
df.count()
```

```
Open          3169
High          3169
Low           3169
Close          3169
Volume         3169
Adj Close      3169
dtype: int64
```

df.ix['2015-12-31']

```
df.ix['2015-12-31']
```

```
Open          7.695000e+02
High          7.695000e+02
Low           7.583400e+02
Close          7.588800e+02
Volume         1.489600e+06
Adj Close      7.588800e+02
Name: 2015-12-31 00:00:00, dtype: float64
```

```
df.to_csv('2330.TW.Yahoo.Finance.Data.csv')
```

```
2330.TW.Yahoo.Finance.Data.csv *
```

	Date	Open	High	Low	Close	Volume	Adj Close
1	2010-01-01	64.5	64.5	64.5	64.5	0	52.8308
2	2010-01-04	65.0	65.0	64.0	64.9	39407000	53.1584
3	2010-01-05	65.0	65.1	63.9	64.5	37138000	52.8308
4	2010-01-06	64.5	64.9	63.7	64.9	49261000	53.1584
5	2010-01-07	64.9	65.0	64.2	64.2	42134000	52.5851
6	2010-01-08	63.5	64.3	63.5	64.0	46076000	52.4213
7	2010-01-11	64.0	64.9	63.5	64.5	36799000	52.8308
8	2010-01-12	64.4	64.4	63.3	63.6	49853000	52.0936
9	2010-01-13	63.0	63.1	62.6	62.8	47976000	51.4384
10	2010-01-14	63.6	63.6	63.0	63.2	36149000	51.766
11	2010-01-15	62.9	63.5	62.8	63.5	47852000	52.0117
12	2010-01-18	62.8	63.1	62.8	62.9	30136000	51.5203
13	2010-01-19	63.0	63.2	62.0	62.5	47202000	51.1926
14	2010-01-20	62.9	63.2	62.2	63.0	52281000	51.6022

```

import fix_yahoo_finance as yf
data = yf.download("^TWII", start="2017-07-01", end="2017-11-15")
data.to_csv('TWII_201707_201711.csv')
data.tail()

```

```

import fix_yahoo_finance as yf
data = yf.download("TWII", start="2017-07-01", end="2017-11-15")
data.to_csv('TWII_201707_201711.csv')
data.tail()

```

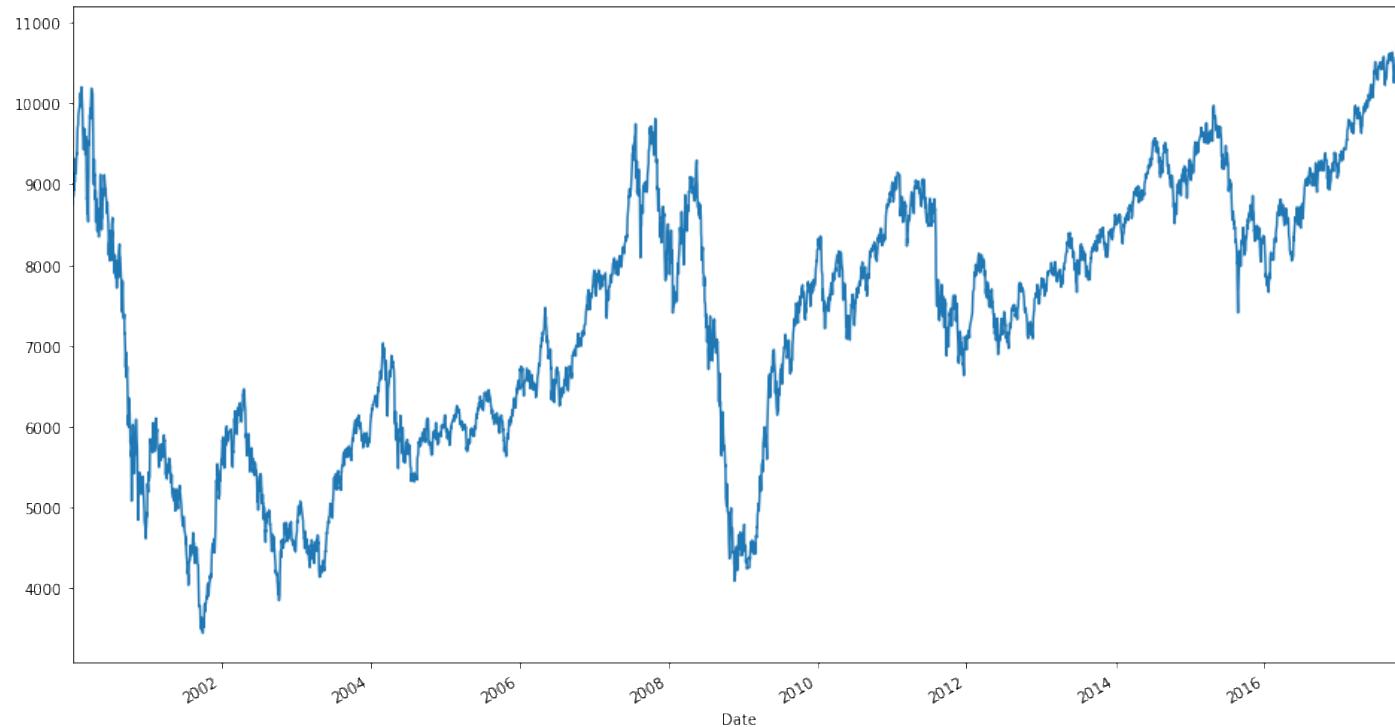
[*****100%*****] 1 of 1 downloaded

	Open	High	Low	Close	Adj Close	Volume
Date						
2017-11-08	10839.440430	10844.740234	10806.009766	10818.990234	10818.990234	2438000
2017-11-09	10802.950195	10831.379883	10721.870117	10743.269531	10743.269531	2917800
2017-11-10	10713.669922	10742.610352	10659.290039	10732.669922	10732.669922	2277000
2017-11-13	10728.219727	10749.389648	10683.919922	10683.919922	10683.919922	2765100
2017-11-14	10716.589844	10735.080078	10654.580078	10687.179688	10687.179688	2596600

df.loc[start:end]

```
df = df.loc['2017-10-01':'2017-11-15']
```

```
import matplotlib.pyplot as plt
%matplotlib inline
import fix_yahoo_finance as yf
df = yf.download("^TWII", start="2000-01-01", end="2017-11-15")
df.to_csv('YF_TWII_2000_2017.csv')
print(df.head())
fig = plt.figure(figsize=(16,9))
df["Adj Close"].plot()
fig.show()
```



candlestick_ohlc

```
import matplotlib.pyplot as plt  
  
from matplotlib.finance  
import candlestick_ohlc
```

```
import matplotlib.pyplot as plt  
from matplotlib.finance import candlestick_ohlc
```



daily_to_weekly

```
#Convert Daily Data to Weekly Data
def daily_to_weekly(df):
    #dfWeekly = daily_to_weekly(df)
    #df.sort_index(axis=0, level=None, ascending=True, inplace=True)
    Open = df.Open.resample('W-Fri').first() #W #W-MON #W-Fri
    High = df.High.resample('W-Fri').max()
    Low = df.Low.resample('W-Fri').min()
    Close = df.Close.resample('W-Fri').last()
    Volume = df.Volume.resample('W-Fri').sum()
    Adj_Close = df["Adj Close"].resample('W-Fri').last()
    dfWeekly = pd.concat([Open, High, Low, Close, Volume, Adj_Close], axis=1)
    dfWeekly = dfWeekly[pd.notnull(dfWeekly['Adj Close'])]
    return dfWeekly
```

daily_to_monthly

```
#Convert Daily Data to Monthly Data
def daily_to_monthly(df):
    #dfMonthly = daily_to_monthly(df)
    Open = df.Open.resample('M').first()
    High = df.High.resample('M').max()
    Low = df.Low.resample('M').min()
    Close = df.Close.resample('M').last()
    Volume = df.Volume.resample('M').sum()
    Adj_Close = df["Adj Close"].resample('M').last()
    dfMonthly = pd.concat([Open, High, Low, Close, Volume, Adj_Close], axis=1)
    dfMonthly = dfMonthly[pd.notnull(dfMonthly['Adj Close'])]
    return dfMonthly
```

TA-Lib: Technical Analysis Library



TA-Lib : Technical Analysis Library

Multi-Platform Tools for Market Analysis ...

TA-Lib is widely used by trading software developers requiring to perform technical analysis of financial market data.

- Includes 200 indicators such as ADX, MACD, RSI, Stochastic, Bollinger Bands etc... ([more info](#))
- Candlestick pattern recognition
- Open-source API for C/C++, Java, Perl, Python and 100% Managed .NET

Free Open-Source Library

TA-Lib is available under a BSD License allowing it to be integrated in your own open-source or commercial application. ([more info](#))

Commercial Application

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Stochastic Oscillator (KD)

```
#Stochastic oscillator %D
def KDJ(df, n, m1, m2):
    #KDJ(df, 9, 3, 3)
    KDJ_n = n
    KDJ_m1 = m1
    KDJ_m2 = m2

    df['Low_n'] = pd.rolling_min(df['Low'], KDJ_n)
    df['Low_n'].fillna(value=pd.expanding_min(df['Low']), inplace=True)
    df['High_n'] = pd.rolling_max(df['High'], KDJ_n)
    df['High_n'].fillna(value=pd.expanding_max(df['High']), inplace=True)

    df['RSV'] = (df['Close'] - df['Low_n']) / (df['High_n'] - df['Low_n']) * 100

    df['KDJ_K'] = pd.ewma(df['RSV'], KDJ_m1)
    df['KDJ_D'] = pd.ewma(df['KDJ_K'], KDJ_m2)
    df['KDJ_J'] = 3 * df['KDJ_K'] - 2 * df['KDJ_D']

    return df
```

Bollinger Bands

```
#Bollinger Bands
def BBANDS20(df, n):
    MA = pd.Series(pd.rolling_mean(df['Close'], n))
    MSD = pd.Series(pd.rolling_std(df['Close'], n))
    b1 = 4 * MSD / MA
    B1 = pd.Series(b1, name = 'BollingerB_' + str(n))
    df = df.join(B1)
    b2 = (df['Close'] - MA + 2 * MSD) / (4 * MSD)
    B2 = pd.Series(b2, name = 'Bollinger%b_' + str(n))
    df = df.join(B2)
    return df
```

Bollinger Bands

```
#BB Bollinger Bands BB_20
def BB_20(df):
    df['BB_MA20'] = pd.stats.moments.rolling_mean(df["Adj Close"], 20)
    df['BB_SD20'] = pd.stats.moments.rolling_std(df['Adj Close'], 20)
    df['BB_UpperBand'] = df['BB_MA20'] + (df['BB_SD20']*2) # Default 2*SD
    df['BB_LowerBand'] = df['BB_MA20'] - (df['BB_SD20']*2)
    df['BB_PB'] = (df['Adj Close'] - df['BB_LowerBand']) / (df['BB_UpperBand'] - df['BB_LowerBand'])
    df['BB_BW'] = (df['BB_UpperBand'] - df['BB_LowerBand']) / df['BB_MA20']
    df['BB_UpperBand_1SD'] = df['BB_MA20'] + (df['BB_SD20'])
    df['BB_LowerBand_1SD'] = df['BB_MA20'] - (df['BB_SD20'])
#BB_PB: Bollinger Band Percent b (PB)
#BB_BW: Bollinger Band Band Width (BW)
return df
```

AI + VDI

POC

AI + VDI POS

TensorFlow Models

- M1: Basic Classification (Image Classification) (65 Seconds)
 - https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/keras/basic_classification.ipynb
- M2: Basic Text Classification (Text Classification) (46 Seconds)
 - https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/keras/basic_text_classification.ipynb
- M3: Basic Regression (Predict House Prices) (43 Seconds)
 - https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/keras/basic_regression.ipynb
- M4: Pix2Pix Eager (Option) (7-8 Hours)
 - https://colab.research.google.com/github/tensorflow/tensorflow/blob/master/tensorflow/contrib/eager/python/examples/pix2pix/pix2pix_eager.ipynb
- M5. NMT with Attention (Option) (20-30 minutes)
 - https://colab.research.google.com/github/tensorflow/tensorflow/blob/master/tensorflow/contrib/eager/python/examples/nmt_with_attention/nmt_with_attention.ipynb

Basic Classification

Fashion MNIST Image Classification

<https://colab.research.google.com/drive/19PJOJi1vn1kjcutlzNHjRSLbeVI4kd5z>

co tf01_basic_classification.ipynb ★

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Train your first neural network: basic classification

Import the Fashion MNIST dataset

Explore the data

Preprocess the data

Build the model

Setup the layers

Compile the model

Train the model

Evaluate accuracy

Make predictions

SECTION

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▼ Train your first neural network: basic classification

 View on TensorFlow.org  Run in Google Colab  View source on GitHub

This guide trains a neural network model to classify images of clothing, like sneakers and shirts. It's okay if you don't understand all the details, this is a fast-paced overview of a complete TensorFlow program with the details explained as we go.

This guide uses [tf.keras](#), a high-level API to build and train models in TensorFlow.

```
1 # memory footprint support libraries/code
2 !ln -sf /opt/bin/nvidia-smi /usr/bin/nvidia-smi
3 !pip install gputil
4 !pip install psutil
5 !pip install humanize
6 import psutil
7 import humanize
8 import os
9 import GPUtil as GPU
10 GPUs = GPU.getGPUs()
11 gpu = GPUs[0]
12 def printm():
13     process = psutil.Process(os.getpid())
14     print("Gen RAM Free: " + humanize.naturalsize( psutil.virtual_memory().available ), " | Pro")
15     print("GPU RAM Free: {0:.0f}MB | Used: {1:.0f}MB | Util {2:.0f}% | Total {3:.0f}MB".format
16 printm()
```

Text Classification

IMDB Movie Reviews

https://colab.research.google.com/drive/1x16h1GhHsLlrLYtPCvCHaoO1W-i_gror

co tf02_basic-text-classification.ipynb ☆

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Text classification with movie reviews

 [View on TensorFlow.org](#)  [Run in Google Colab](#)  [View source on GitHub](#)

This notebook classifies movie reviews as *positive* or *negative* using the text of the review. This is an example of *binary*—or two-class—classification, an important and widely applicable kind of machine learning problem.

We'll use the [IMDB dataset](#) that contains the text of 50,000 movie reviews from the [Internet Movie Database](#). These are split into 25,000 reviews for training and 25,000 reviews for testing. The training and testing sets are *balanced*, meaning they contain an equal number of positive and negative reviews.

This notebook uses `tf.keras`, a high-level API to build and train models in TensorFlow. For a more advanced text classification tutorial using `tf.keras`, see the [MLCC Text Classification Guide](#).

```
1 # memory footprint support libraries/code
2 !ln -sf /opt/bin/nvidia-smi /usr/bin/nvidia-smi
3 !pip install gputil
4 !pip install psutil
5 !pip install humanize
6 import psutil
7 import humanize
8 import os
9 import GPUUtil as GPU
10 GPUs = GPU.getGPUs()
11 gpu = GPUs[0]
12 def printm():
    processes = psutil.Processes(os.getpid())
13
```

Source: https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/keras/basic_text_classification.ipynb

Basic Regression

Predict House Prices

https://colab.research.google.com/drive/1v4c8ZHTnRtgd2_25K_AURjR6SCVBRdlj

CO tf03_basic-regression.ipynb 

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CONNECT EDITING

Table of contents Code snippets Files X

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Predict house prices: regression

The Boston Housing Prices dataset

Examples and features

Labels

Normalize features

Create the model

Train the model

Predict

Conclusion

+ SECTION

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View on TensorFlow.org Run in Google Colab View source on GitHub

In a *regression* problem, we aim to predict the output of a continuous value, like a price or a probability. Contrast this with a *classification* problem, where we aim to predict a discrete label (for example, where a picture contains an apple or an orange).

This notebook builds a model to predict the median price of homes in a Boston suburb during the mid-1970s. To do this, we'll provide the model with some data points about the suburb, such as the crime rate and the local property tax rate.

This example uses the `tf.keras` API, see [this guide](#) for details.

```
# memory footprint support libraries/code
!ln -sf /opt/bin/nvidia-smi /usr/bin/nvidia-smi
!pip install gputil
!pip install psutil
!pip install humanize
import psutil
import humanize
import os
import GPUUtil as GPU
GPUs = GPU.getGPUs()
gpu = GPUs[0]
def printm():
    process = psutil.Process(os.getpid())
    print("Gen RAM Free: " + humanize.naturalsize( psutil.virtual_memory().available ), " | Proc size: "
    print("GPU RAM Free: {0:.0f}MB | Used: {1:.0f}MB | Util {2:.0f}% | Total {3:.0f}MB".format(gpu.memo
```

AI+VDI POC

ISAC+TKU Test

- AI+VDI POC Folder (3+1 ipynb) (v3.0.20181120)
 - <https://drive.google.com/open?id=1qHOemktbEmUz-ot8eFxIKbGwJvXlrjtc>
- run3models.ipynb
 - https://colab.research.google.com/drive/1HQ1GrIqQUUPCct7_AVgoMwMrh0UqMm0f
- AI+VDI POC ISAC+TKU Test Report
 - <https://docs.google.com/spreadsheets/d/1meMwqn15PSuTk6d5TgendDpdDX6L3OfHM4E0Slkq1Zk/edit?usp=sharing>

Summary

- Prescriptive Analytics
- Model-Based Decision Making
- Structure of Mathematical Models for Decision Support
- Certainty, Uncertainty, and Risk
- Mathematical Programming Optimization
- Simulation

References

- Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson.
- Jake VanderPlas (2016), Python Data Science Handbook: Essential Tools for Working with Data, O'Reilly Media.