ML 툴 비교

부재: Linear Model

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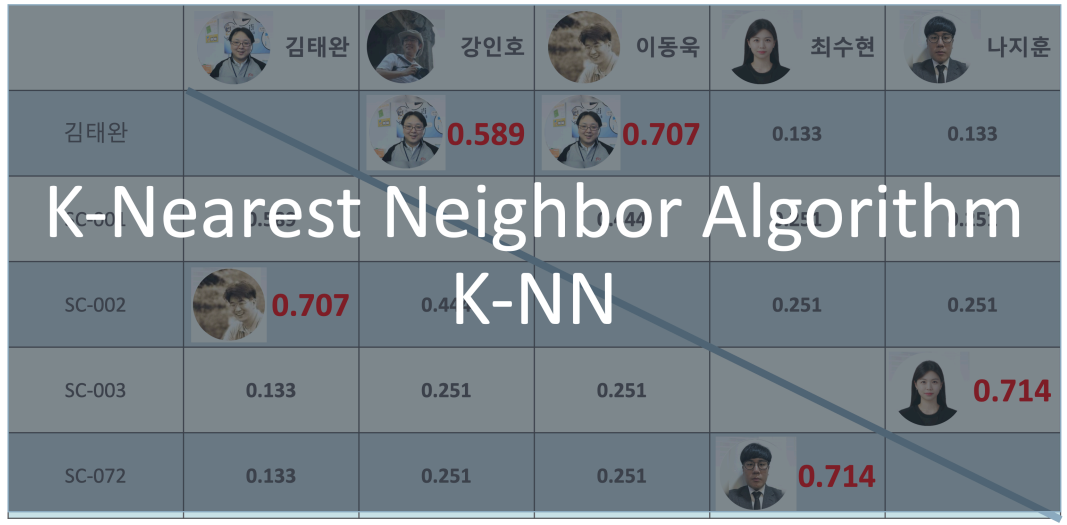
ORACLE

2018.06 SE All Seminar – AI/ML on OCI

김태완과 비슷한 SE를 찾아라: 유사도 측정 결과



 23

2018.07 SE All Seminar – Spark on OCI

Oracle Big Data Services on OCI

Big Data Service on OCI

Data Flow

OCI Data Flow offers an ability to run Spark jobs in a secure serverless (no infrastructure to deploy or manage) way in OCI.

SparklineData

SparklineData (planned to be part of OCI Data Flow) enables interactive/OLAP style analysis on very large datasets directly on datalakes in OCI.

클라우드에서 Big Data를 하고자 하는 고객
Cloud Native Big Data
-

클라우드에서 Hadoop을 하고 싶은 고객
- On-premise 연동, CDH 활용 ….
-

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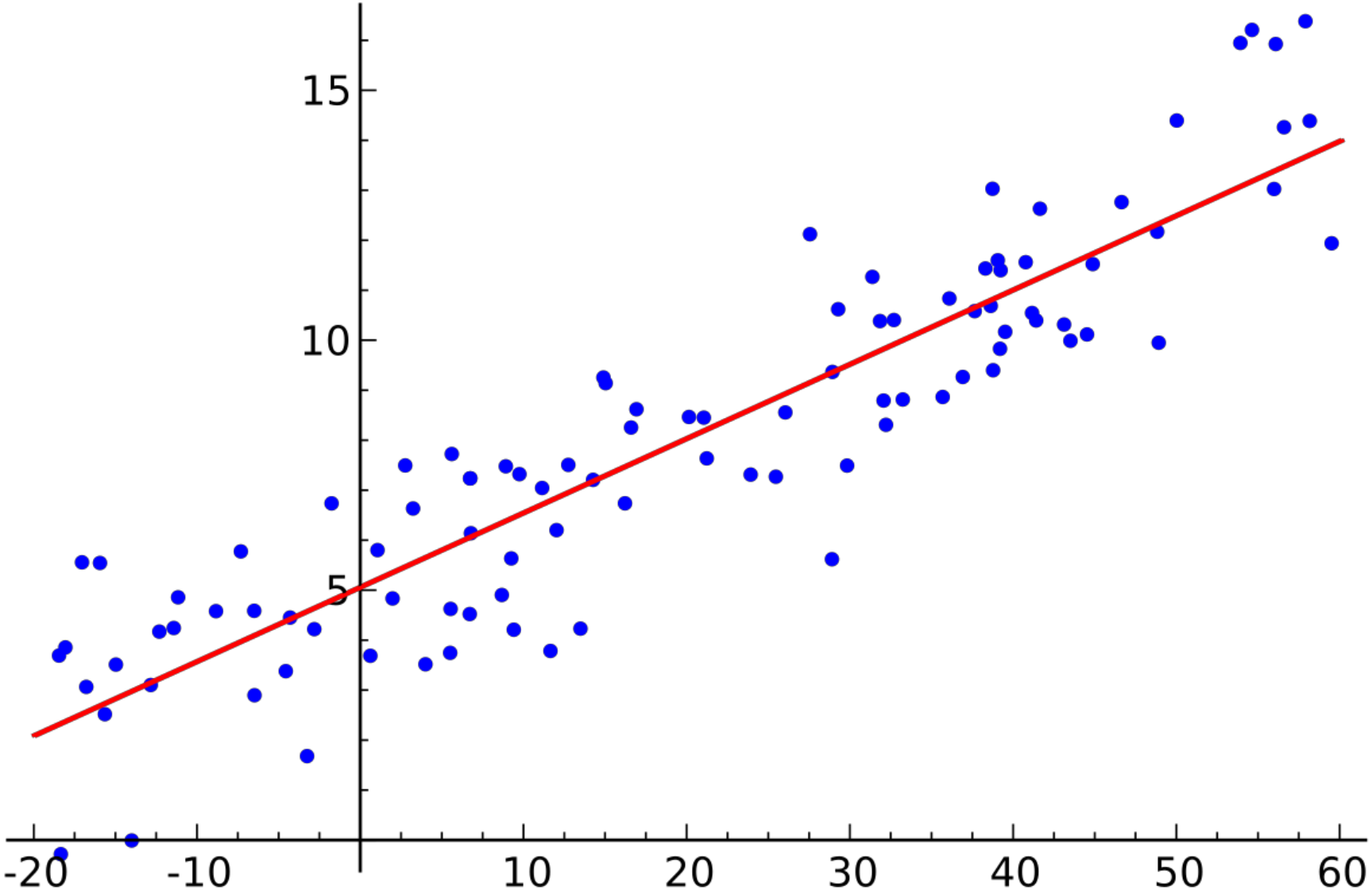
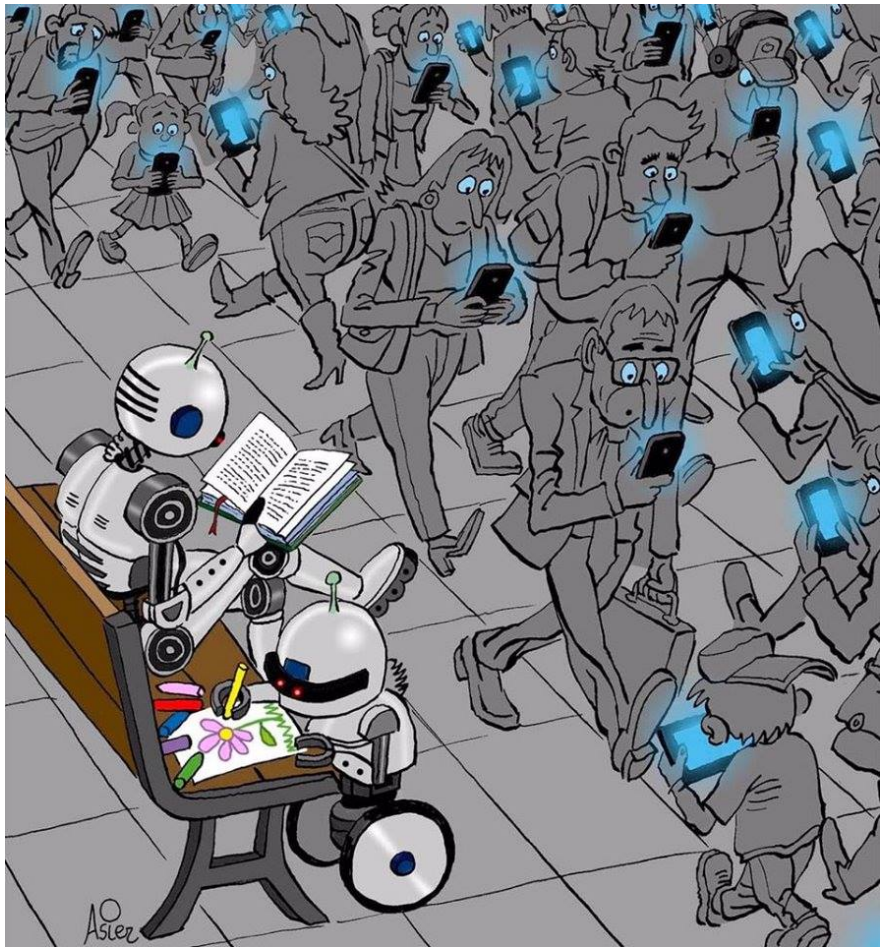
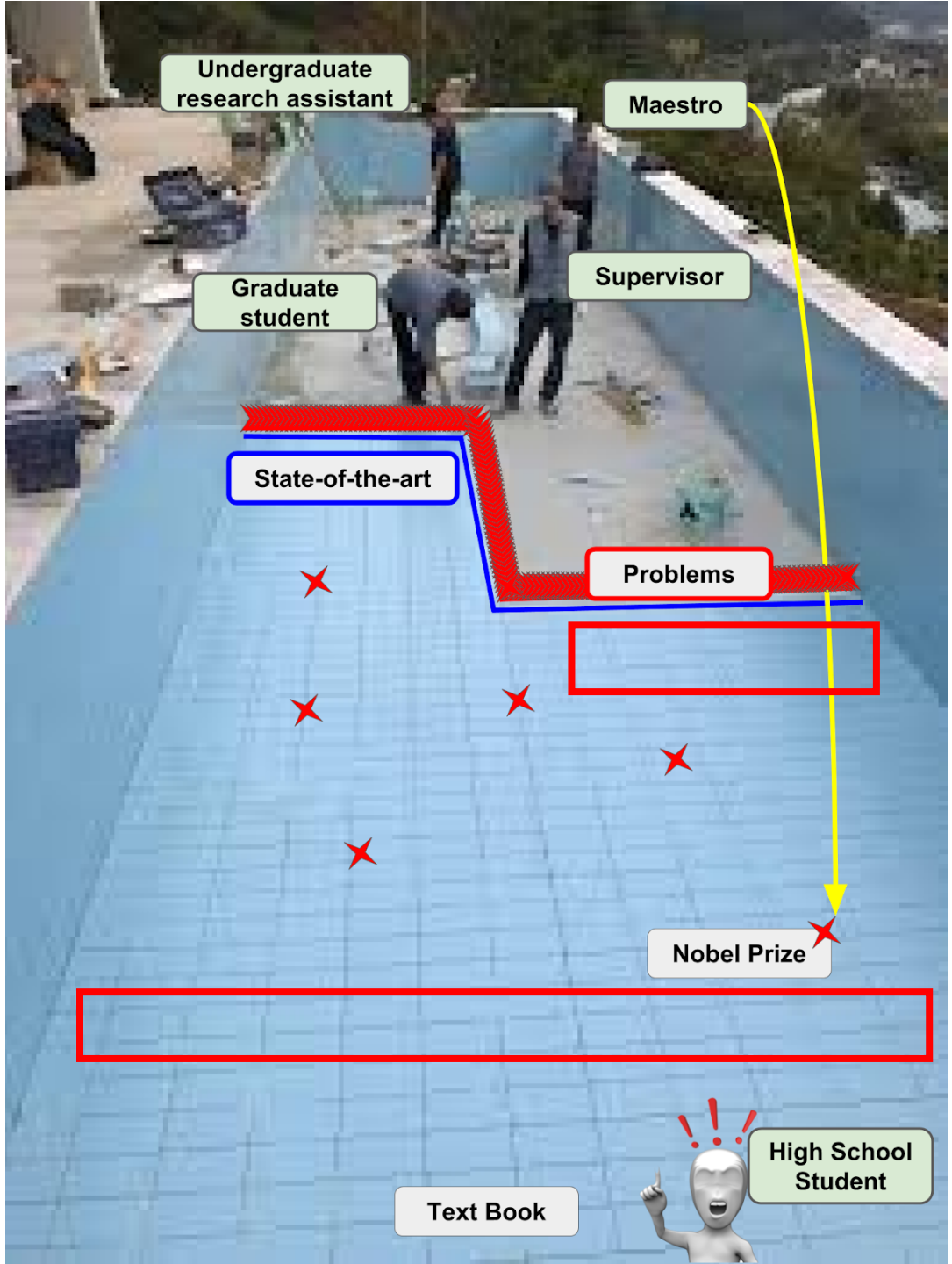


인간과 AI 그리고 ….

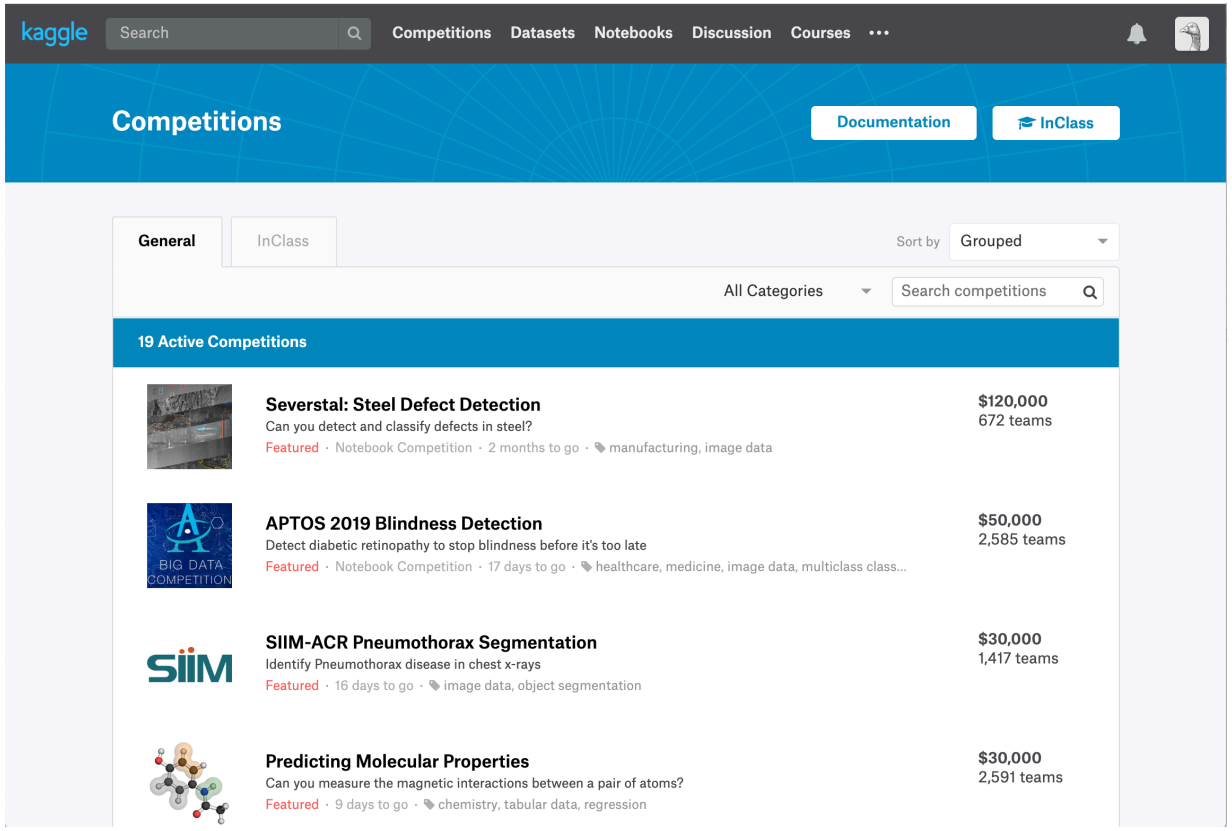


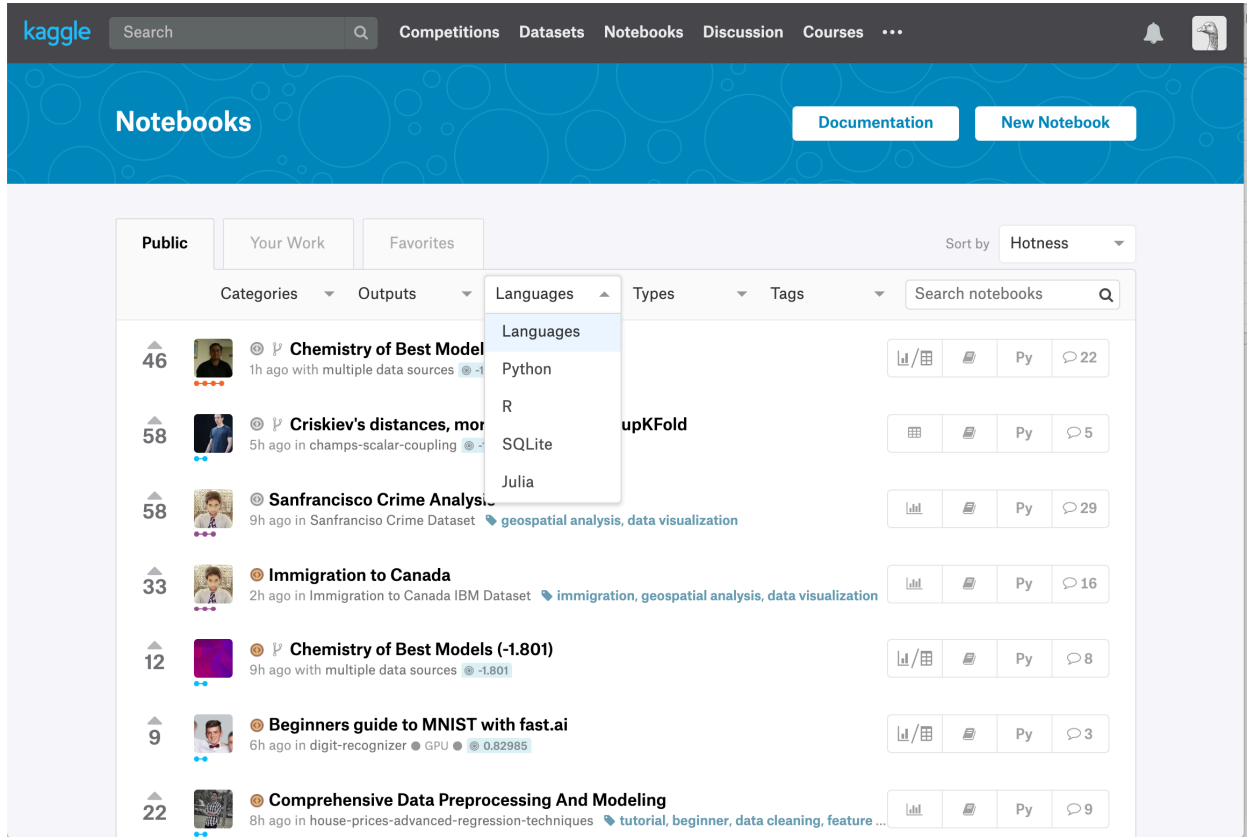
-Oracle Position?
-SE Position?

https://jarche.com/2019/05/a-decade-of-finds/

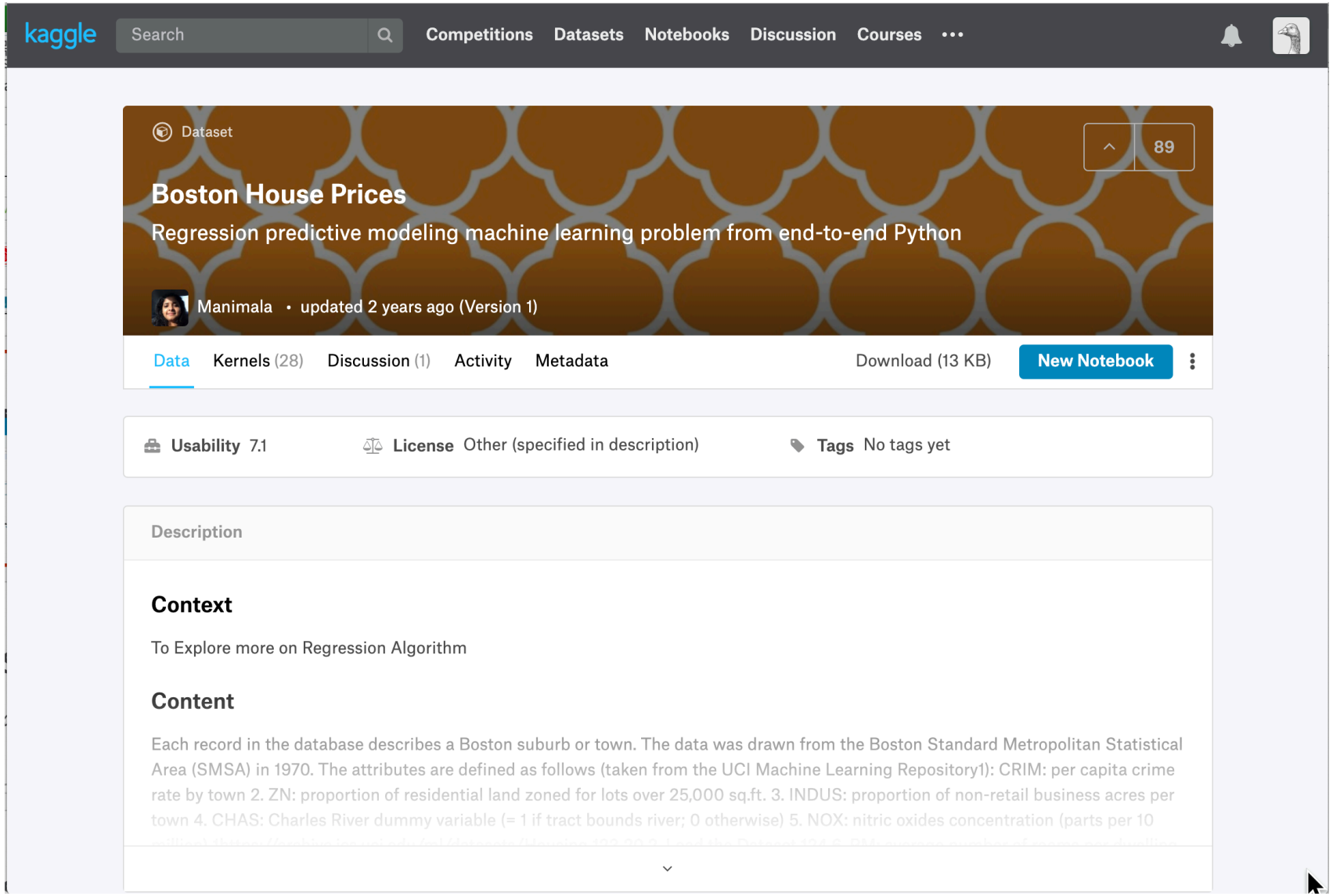

Undergraduate research assistant
Maestro
Graduate student
Supervisor
State-of-the-art
Problems
Nobel Prize
High School Student
Text Book

Kaggle: http://kaggle.com





Kaggle: Boston House Pricing



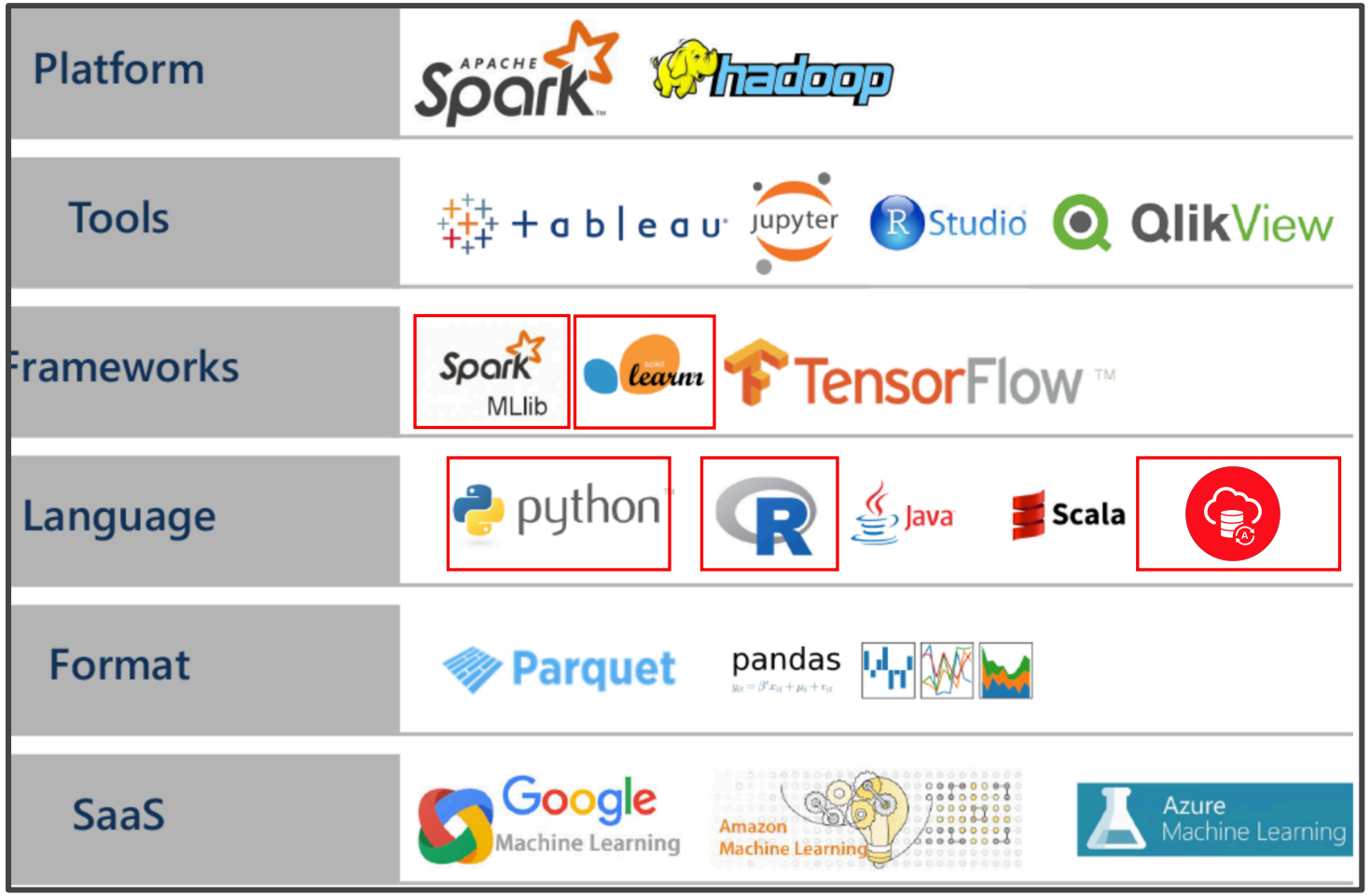
Linear Regression

$$\hat{y} = x_1 w_1 + x_2 w_2 + \cdots + x_n w_n + b$$

Linear Regression

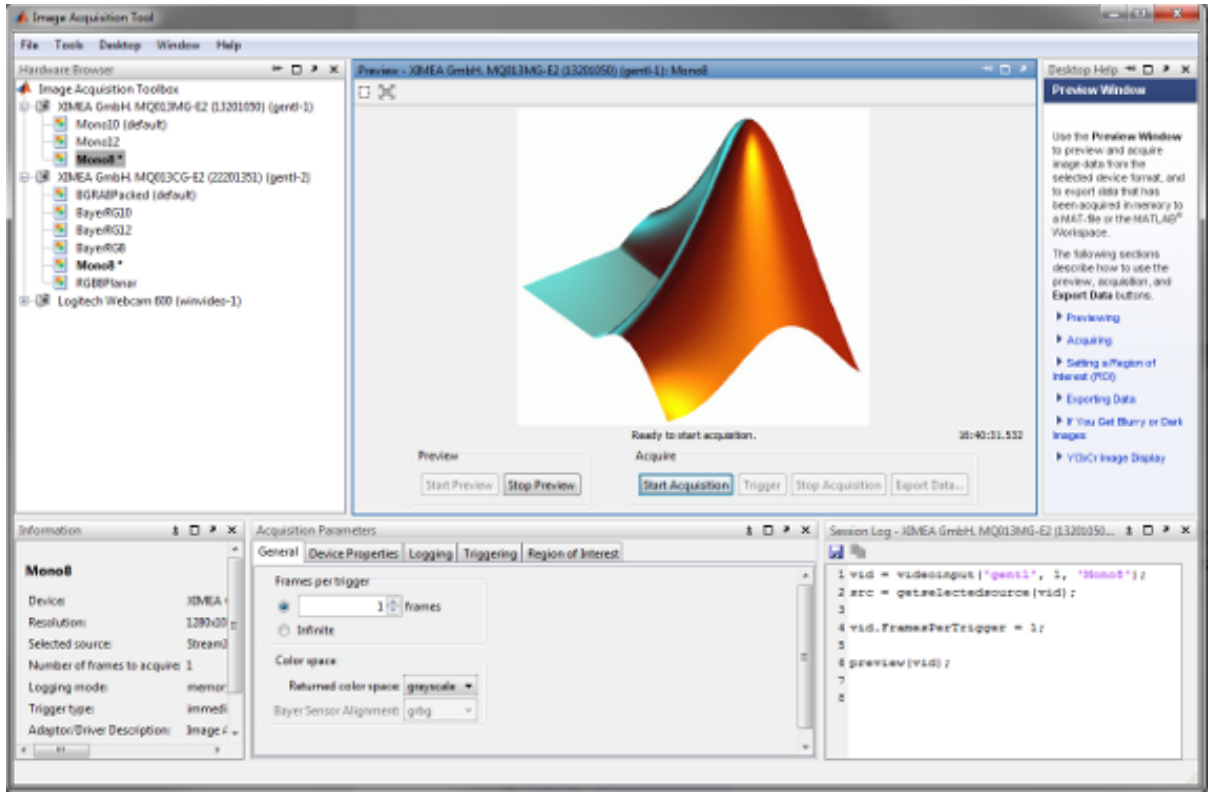
$$\hat{y} = x_1 w_1 + x_2 w_2 + \cdots + x_n w_n + b$$
$$= \sum x_n w_n = WT\mathrm{x}$$

데이터 분석 기술



https://volansys.com/data-science-services/

분석 기술: Matlab



Matt Lee
6분 ·

방금 뉴욕의 개발자 임백준님의 글에 서도 언급 되어 있지만

Matlab은 친청인 학계에서도 슬슬 기피 당하고 나는 진짜 꼭 서보고 싶었지만 그럴 기회 조차도 없었음.
(파이썬,R짱짱맨이야, 그리고 줄리아 슬금슬금 성장중)

나는 아직도 수치해석 때 교수님께서 하신 말씀을 잊지 못한다.

"우리는 코딩 실습 Matlab으로 하지 않습니다."

"왜요 교수님?"

"여러분은 연계 프로젝트(여기서 연계는 다른 학계나 기업,정부와의 연계를 뜻함)용 언어로 쓰지도 못 할 언어를 단 한 두번의 수업을 위해서 배우고 사용 하고 싶나요?"
(한 마디로 좀 심하게 말해서 수학과나 물리학과 빼고는 잘 사용하지도 않는 죽은 고인물의 언어라는 뜻...)

"....."

Matlab 지못미ㅠㅠ

그와 중에 가격은 엄청 비싸서 졸업과 동시에 쓰지도 못함;;;

1

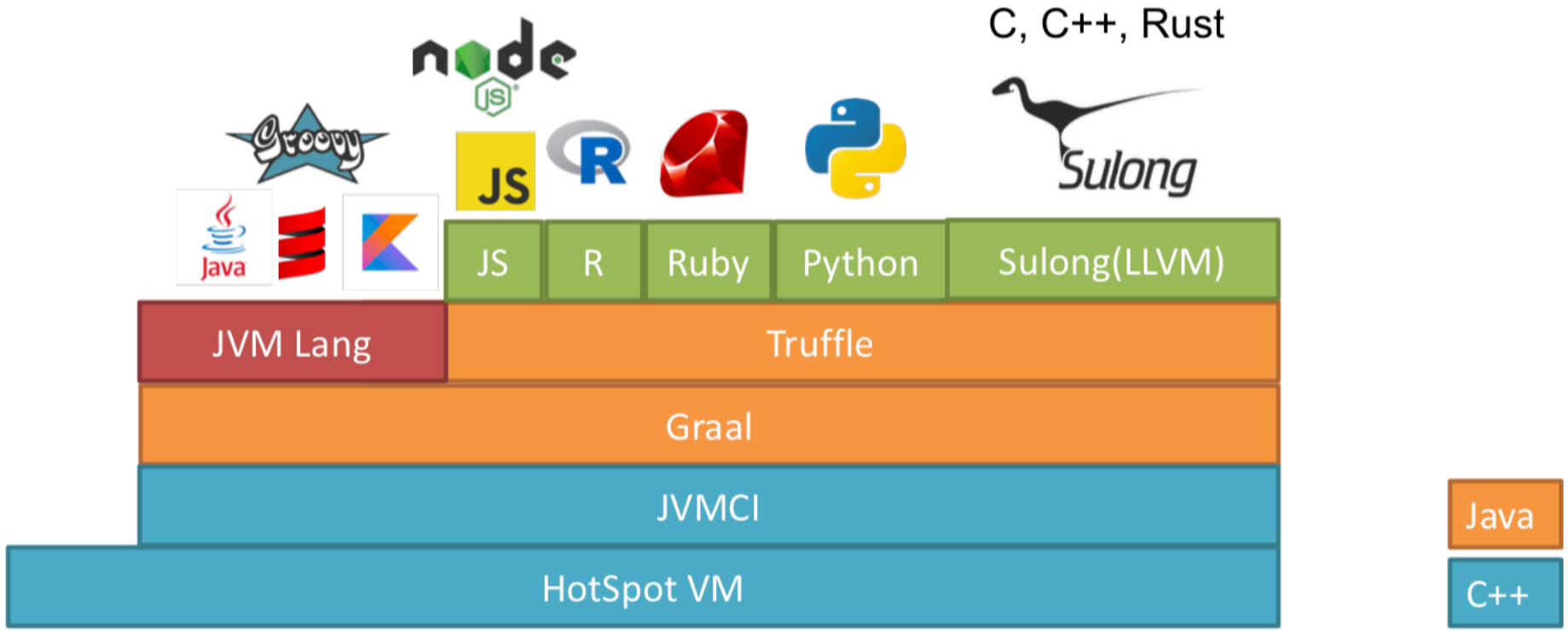
분석 기술:R

데이터 분석 / 시각화를 위한 전용언어

-

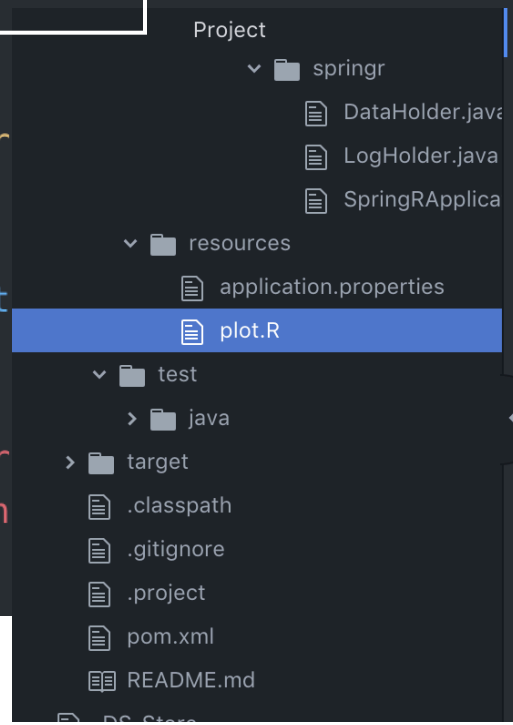
- 학습 용이
- 언어 구조 단순
- 풍부한 알고리즘
- 확장성 결여

GraalVM & Fast R



spring-r: mvn spring-boot:run

```java
@Controller
@SpringBootApplication
public class SpringRApplication {

  @Value(value = "classpath:plot.R")
  private Resource rSource;

  @Autowired
  private Function<DataHolder, Str

  @Bean
  Function<DataHolder, String> get
    throws IOException {
    Source source =
      Source.newBuilder("R", rSour
    return ctx.eval(source).as(Fun
  }
```



plot.R

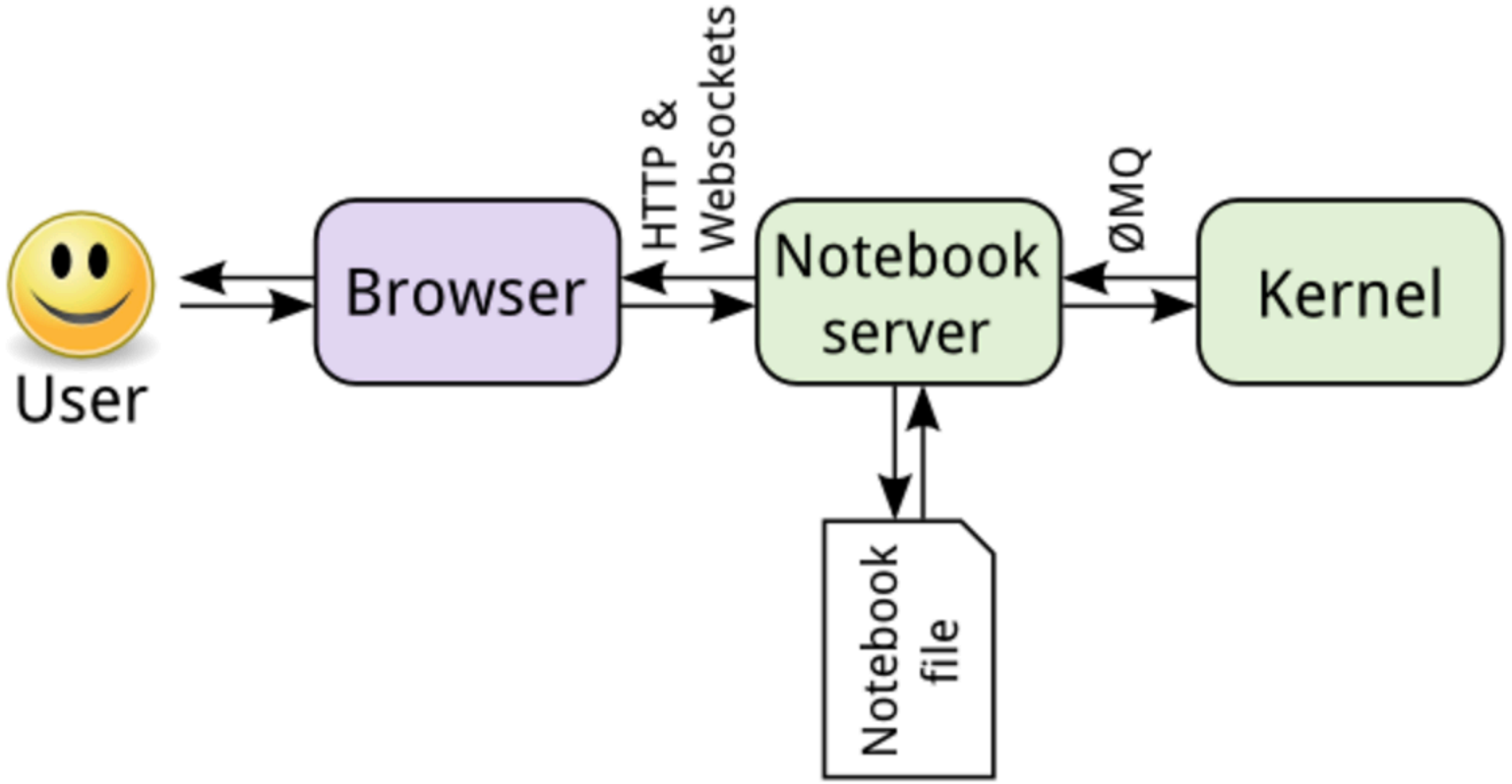
```r
library(ggplot2)
data <<- numeric(100)

function(dataHolder) {
    svg()
    data <<- c(data[2:100], dataHolder$value)

    logHolder <- java.type("org.graalvm.demos.springr.LogHolder")
    logHolder$log(dataHolder$value, data[90:100])

    plot <- ggplot(data = data.frame(systemLoad = data, time = -99:0),
                aes(x=time, y=systemLoad, group=1)) +
                geom_line(color="orange") +
                expand_limits(x=0, y=0)
    print(plot)
    svg.off()
}
```

분석 기술:Python

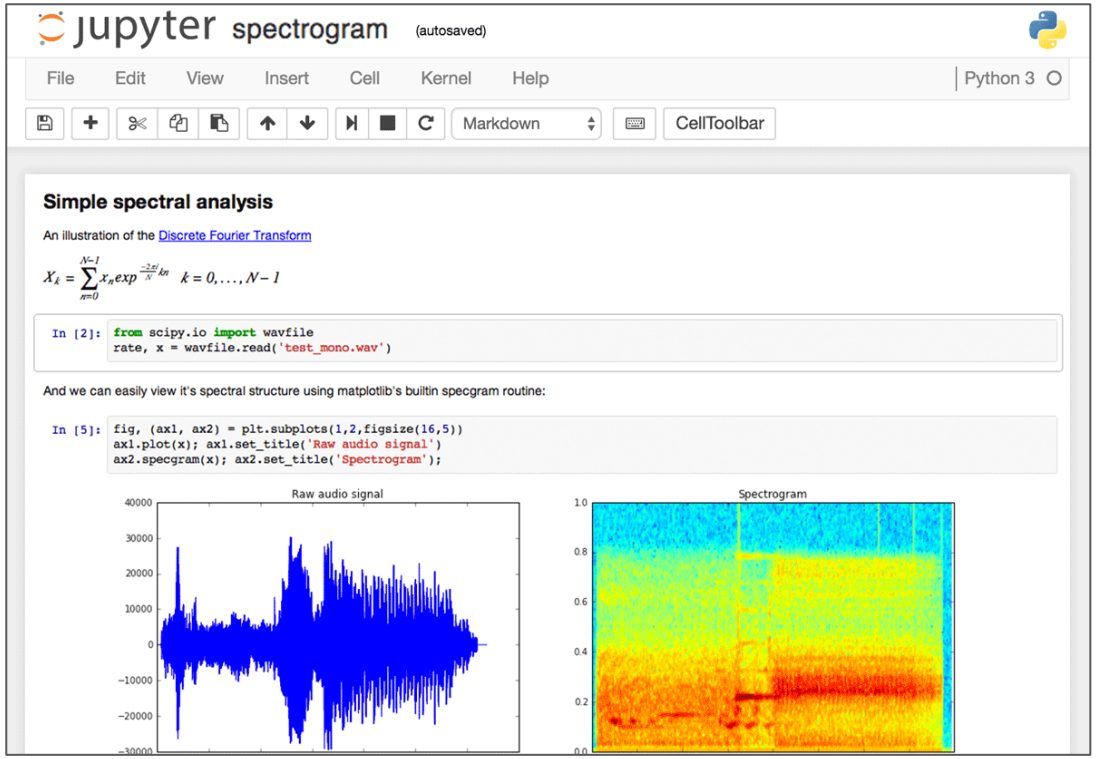
분석 기술: Spark

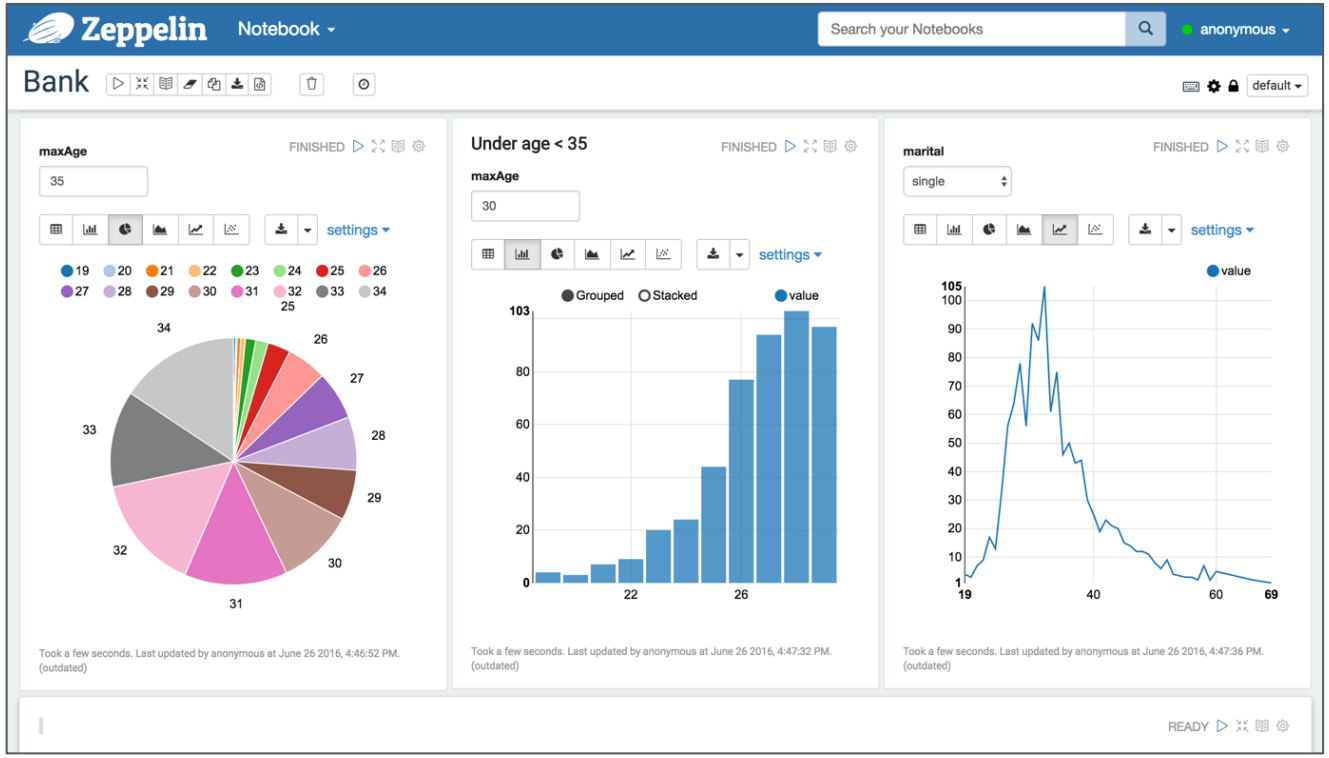
- Sckit- Learn의 영향
- 복잡성 높음
- 기술 난이도 높음
- 개발 난이도 높음

웹기반 분석환경

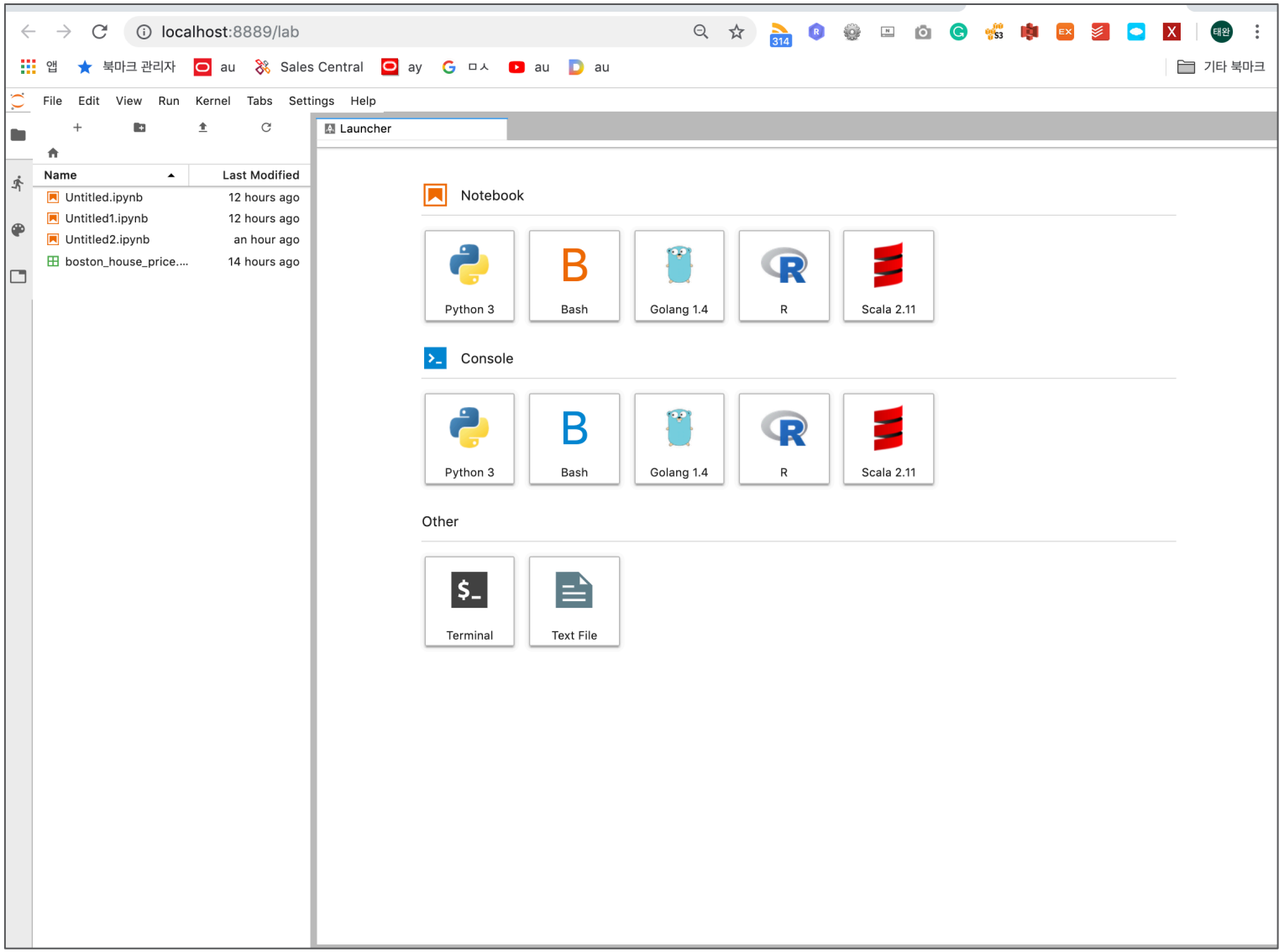


웹기반 분석환경

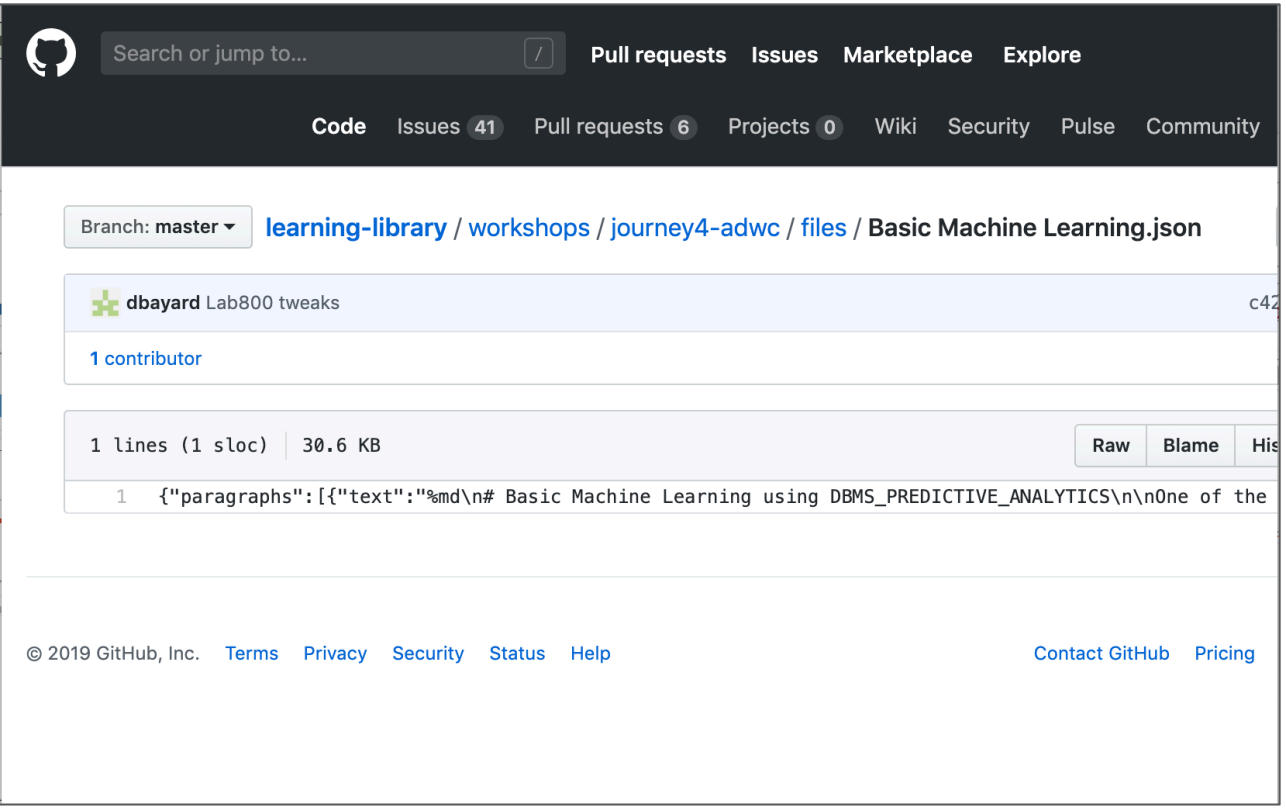


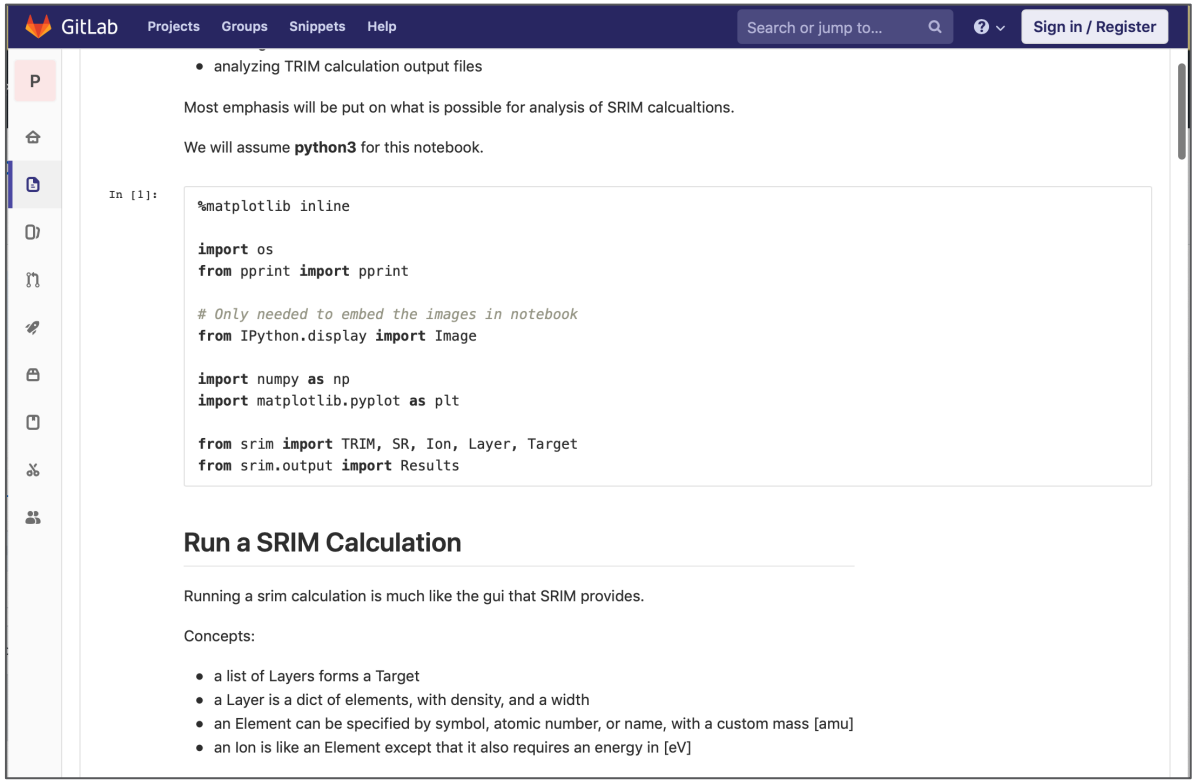


웹기반 분석환경: Jupyter Lab



웹기반 분석환경: Jupyter >> Zeppelin

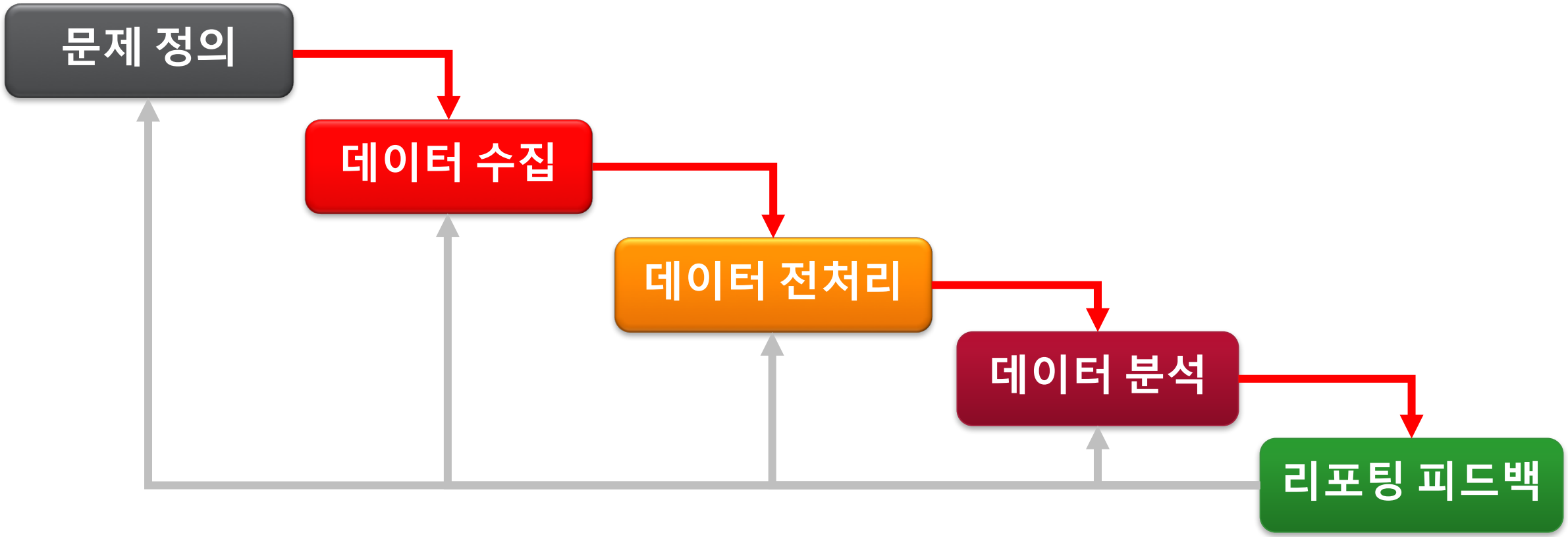




https://github.com/oracle/learning-library/blob/master/workshops/journey4-adwc/files/Basic%20Machine%20Learning.json

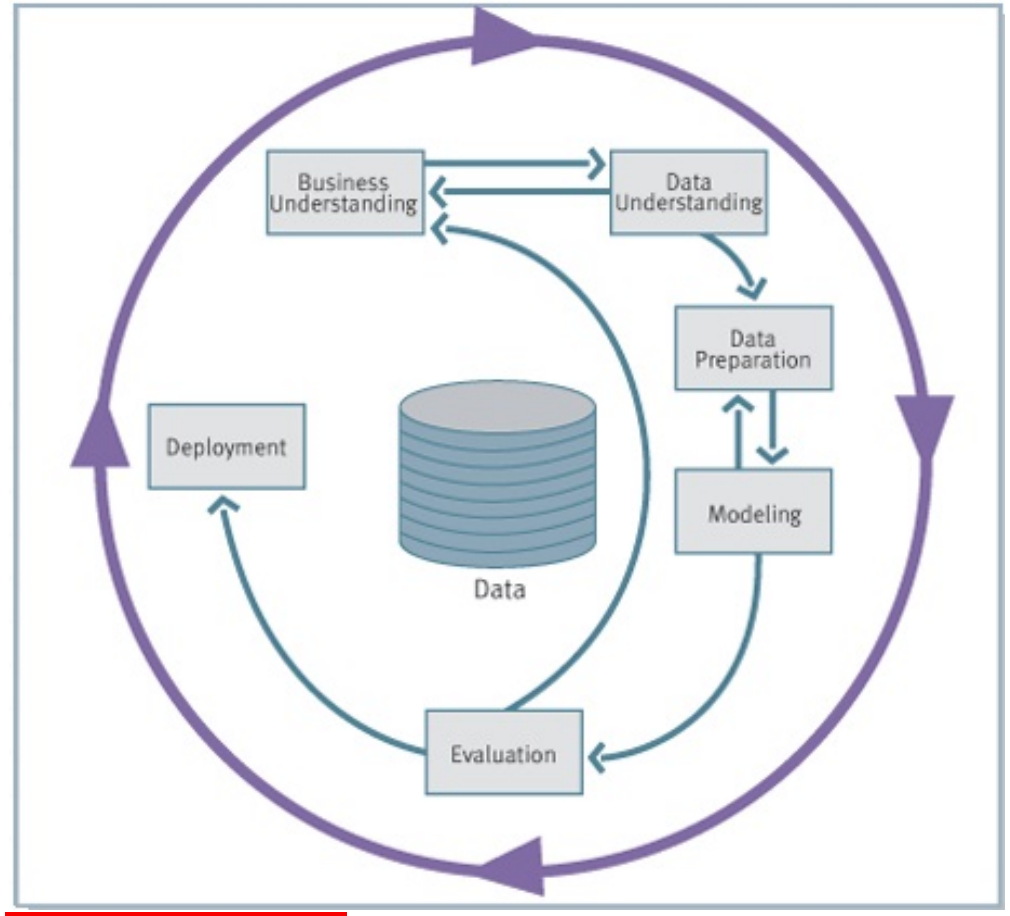
https://gitlab.com/costrouc/pysrim/blob/master/examples/notebooks/Analysis.ipynb

데이터 분석 프로세스

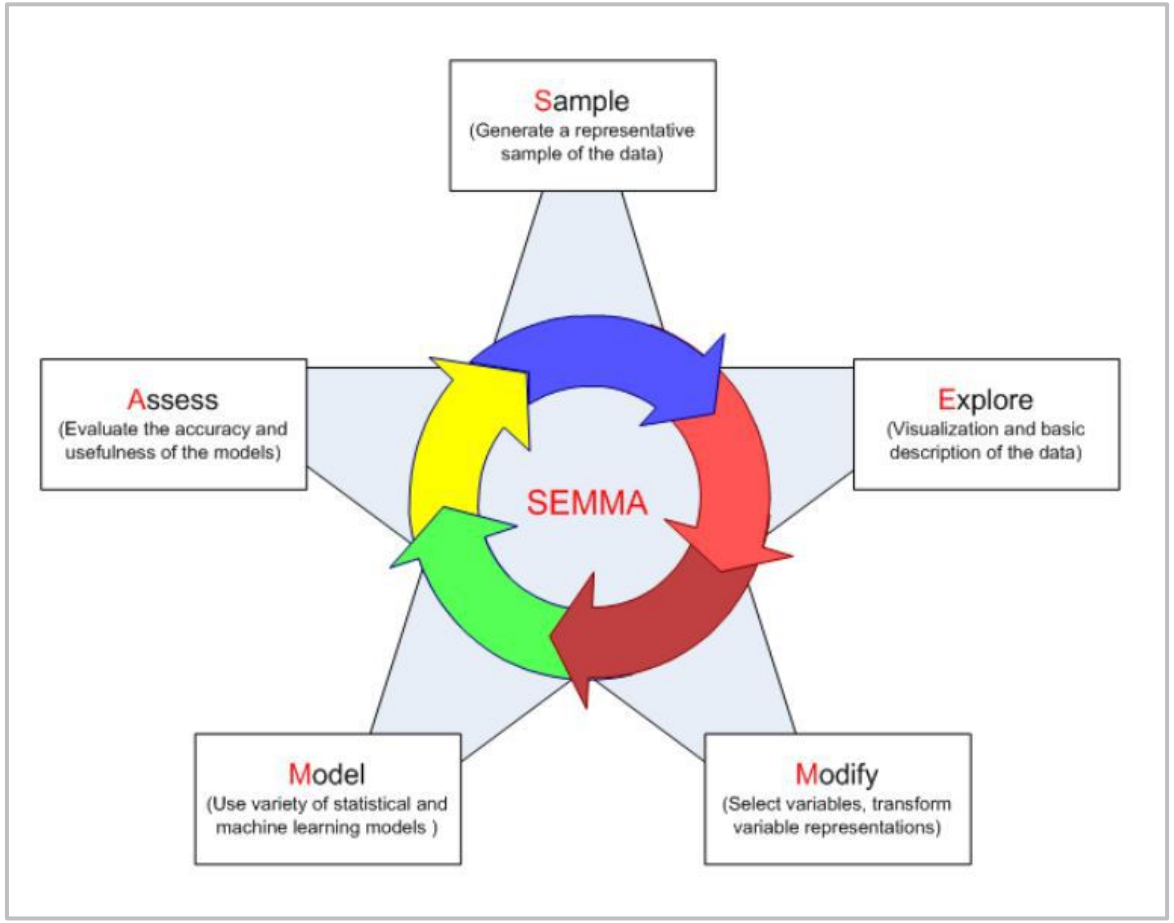


데이터 분석 프로세스: CRISP-DM, SEMMA

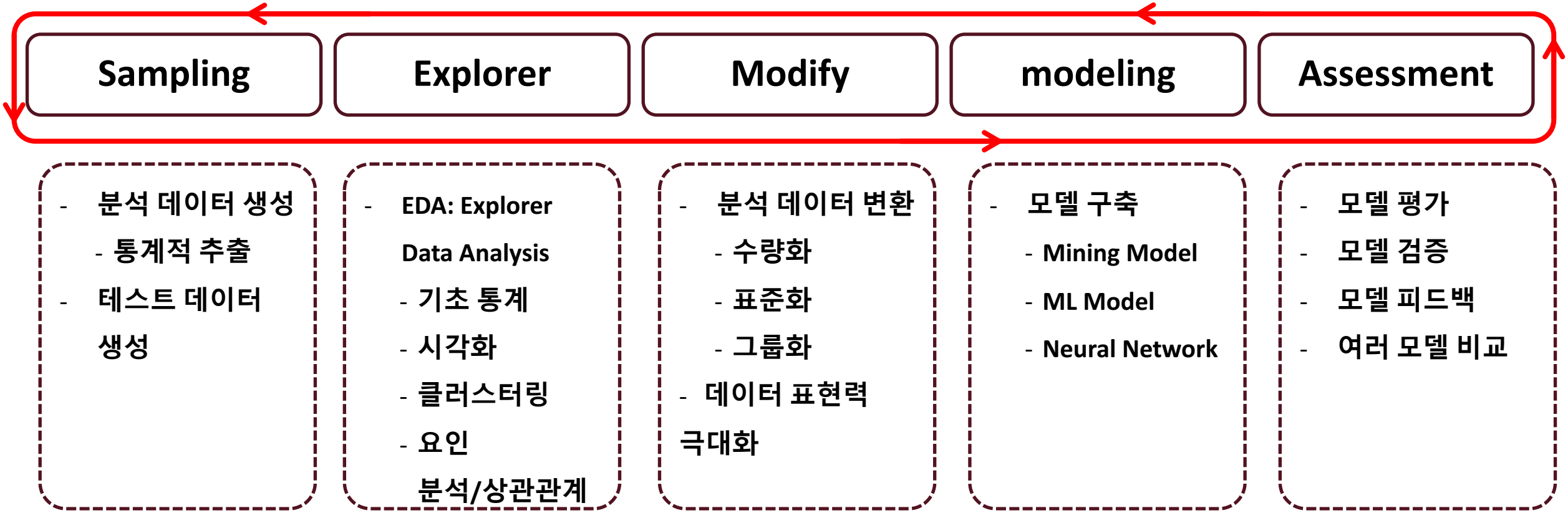
CRISP-DM: 데이터 마이닝 표준



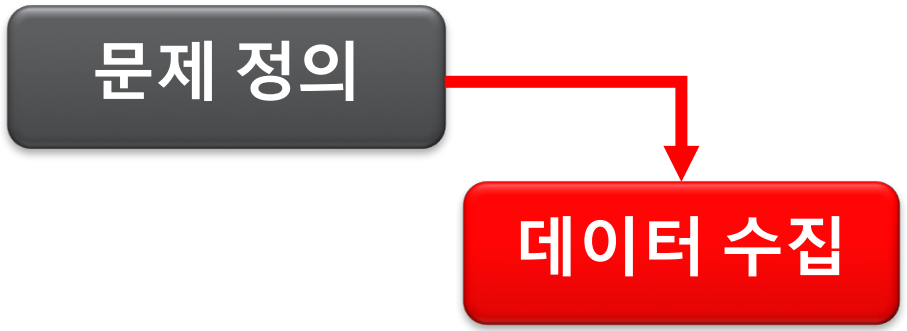
SEMMA: SAS 프로세스



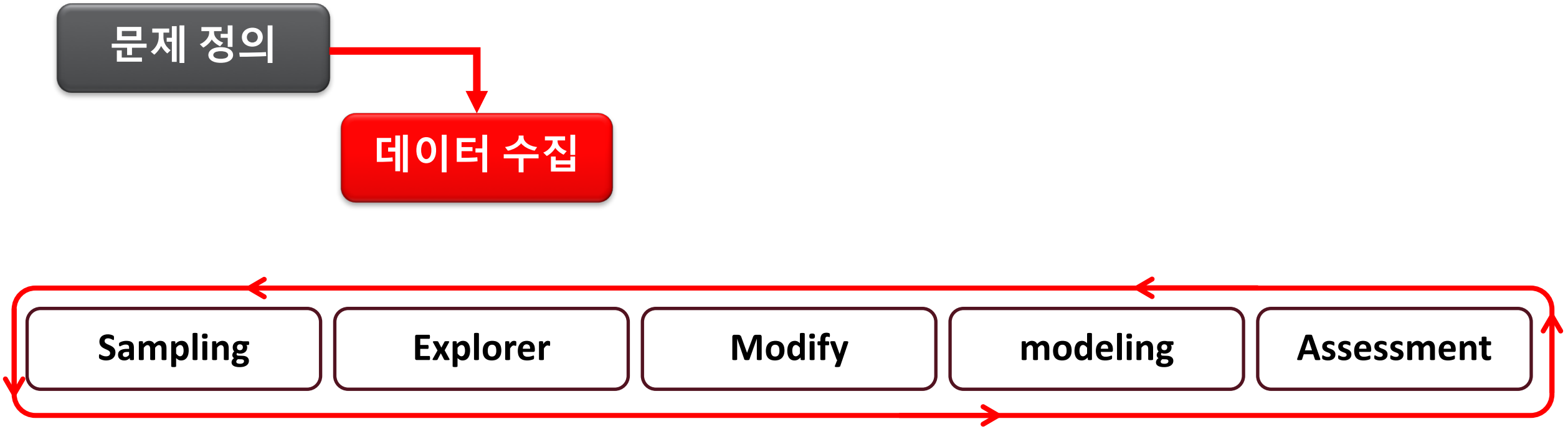
데이터 분석 프로세스: SEMMA



데이터 분석 프로세스



데이터 분석 프로세스



데이터 로딩

[2]:
```
import pandas as pd
boston_df=pd.read_csv("./boston_house_price.csv")
```

[4]:
```
boston_df.head()
```

[4]:

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b	lstat	medv
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	5.33	36.2

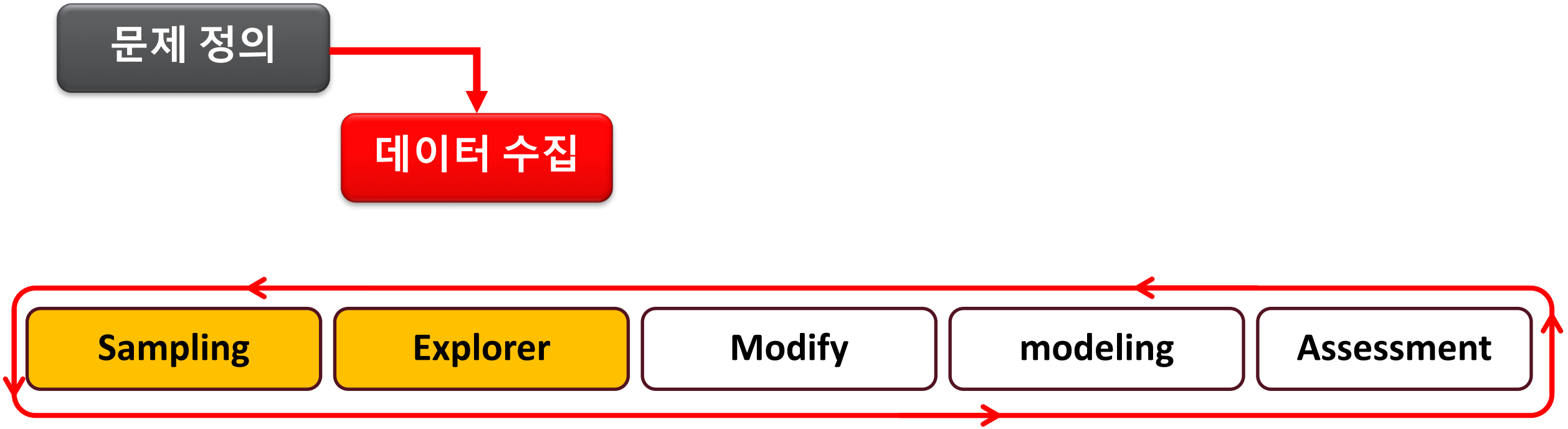
[8]:
```
boston_df.shape
```

[8]:
```
(506, 14)
```

속성

속성	설명
CRIM	자치시(town) 별 1인당 범죄율
ZN	25,000 평방피트를 초과하는 거주지역의 비율
INDUS	비소매상업지역이 점유하고 있는 토지의 비율
CHAS	찰스강에 대한 더미변수(강의 경계에 위치한 경우는 1, 아니면 0)
NOX	10ppm 당 농축 일산화질소
RM	주택 1가구당 평균 방의 개수
AGE	1940년 이전에 건축된 소유 주택의 비율
DIS	5개의 보스턴 직업센터까지의 접근성 지수
RAD	방사형 도로까지의 접근성 지수
TAX	10,000 달러 당 재산세율
PTRATIO	자치시(town)별 학생/교사 비율
B	1000(Bk-0.63)^2, 여기서 Bk는 자치시 별 흑인의 비율을 말함.
LSTAT	모집단의 하위계층의 비율(%)
MEDV	본인 소유의 주택가격(단위: $1,000)

데이터 분석 프로세스



EDA: Explorer Data Analysis

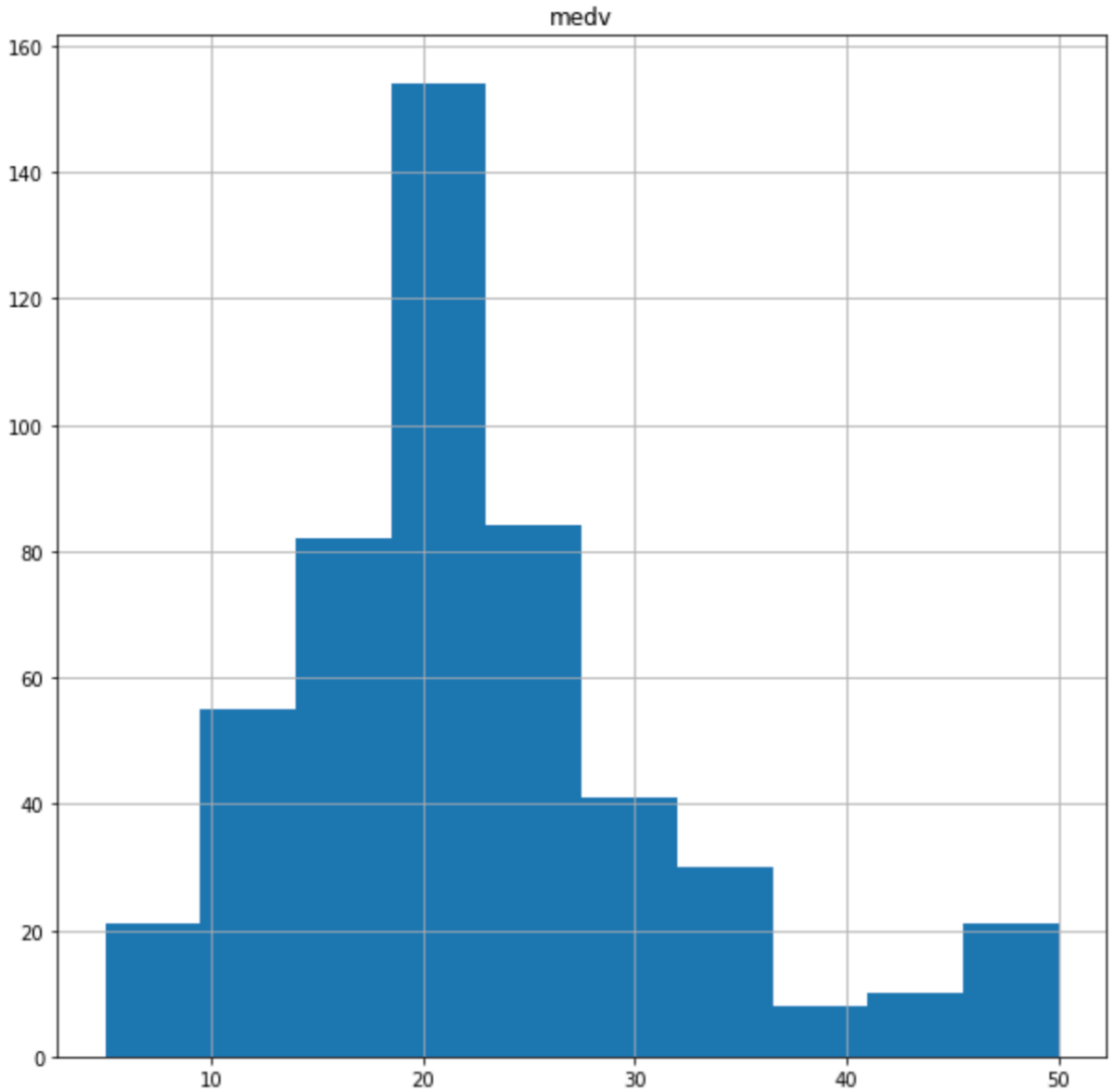
[9]:
```
boston_df.describe()
```

[9]:

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b	lstat	medv
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.237154	18.455534	356.674032	12.653063	22.532806
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.164946	91.294864	7.141062	9.197104
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600000	0.320000	1.730000	5.000000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.400000	375.377500	6.950000	17.025000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.050000	391.440000	11.360000	21.200000
75%	3.677082	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.200000	396.225000	16.955000	25.000000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000	396.900000	37.970000	50.000000

```
In [87]: %matplotlib inline
boston_df.hist("medv", figsize=(10,10))
```

```
Out[87]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x2969e50ac8>]],
       dtype=object)
```

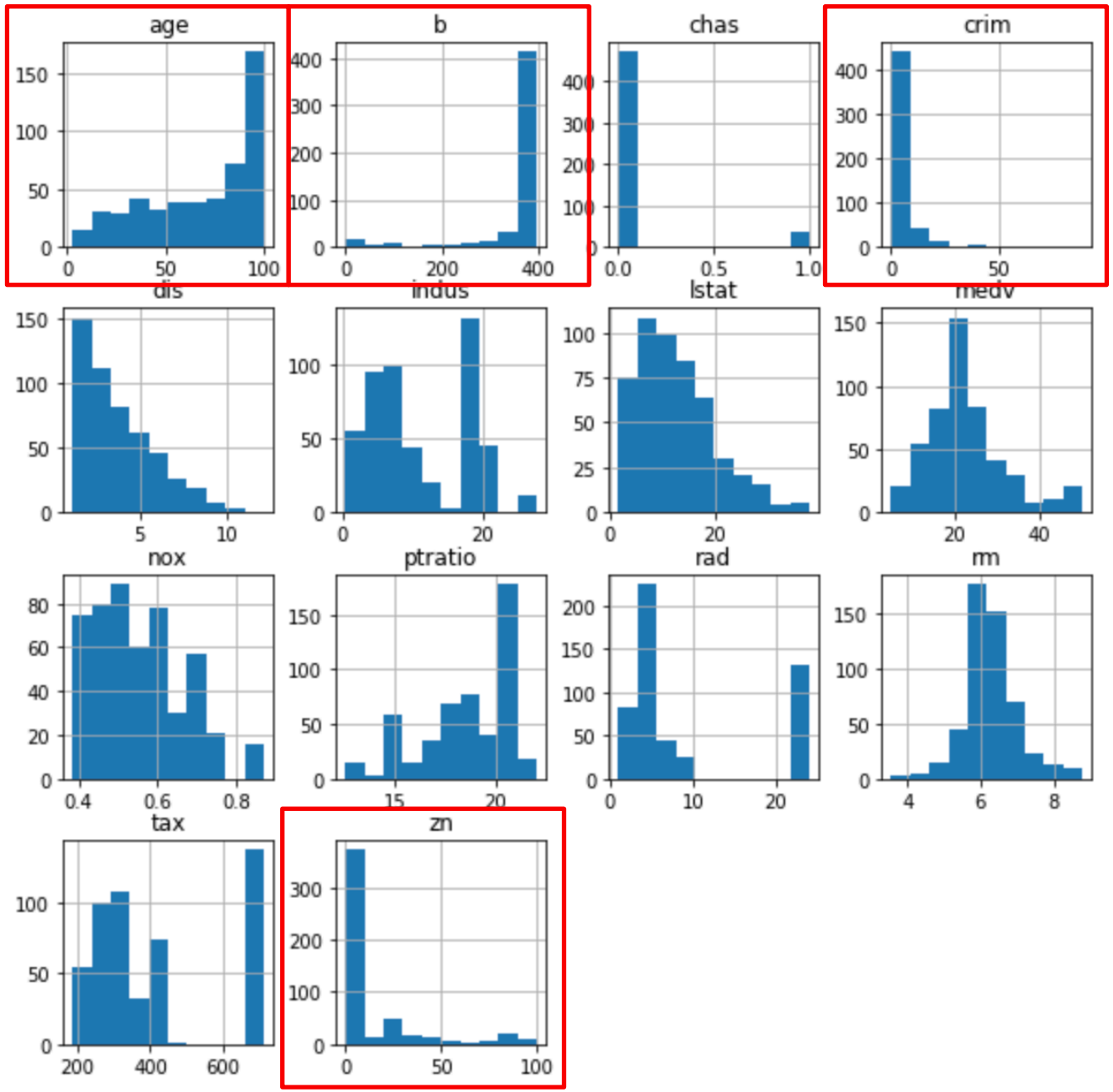



```
boston_df['medv'].describe()
```

```
count    506.000000
mean      22.532806
std        9.197104
min        5.000000
25%       17.025000
50%       21.200000
75%       25.000000
max       50.000000
Name: medv, dtype: float64
```

- 보스턴 집값: 정규 분포에서 벗어난 비대칭성
- 보스턴의 집값은 평균적으로 $22000 (MEDV 평균: 22.5328063)
- 보스턴의 가장 비싼 집값은 $50,000
- 이 값은 Outlier로 구분, 분석에서 제외 (MEDV가 50인 16개의 ROW 제외)
- Outlier 판단은 IQR 방법을 사용, 계산 값을 넘어서는 값을 Outlier로 판단
  - IQR = Q3 – Q1 (50%의 흩어진 정도)

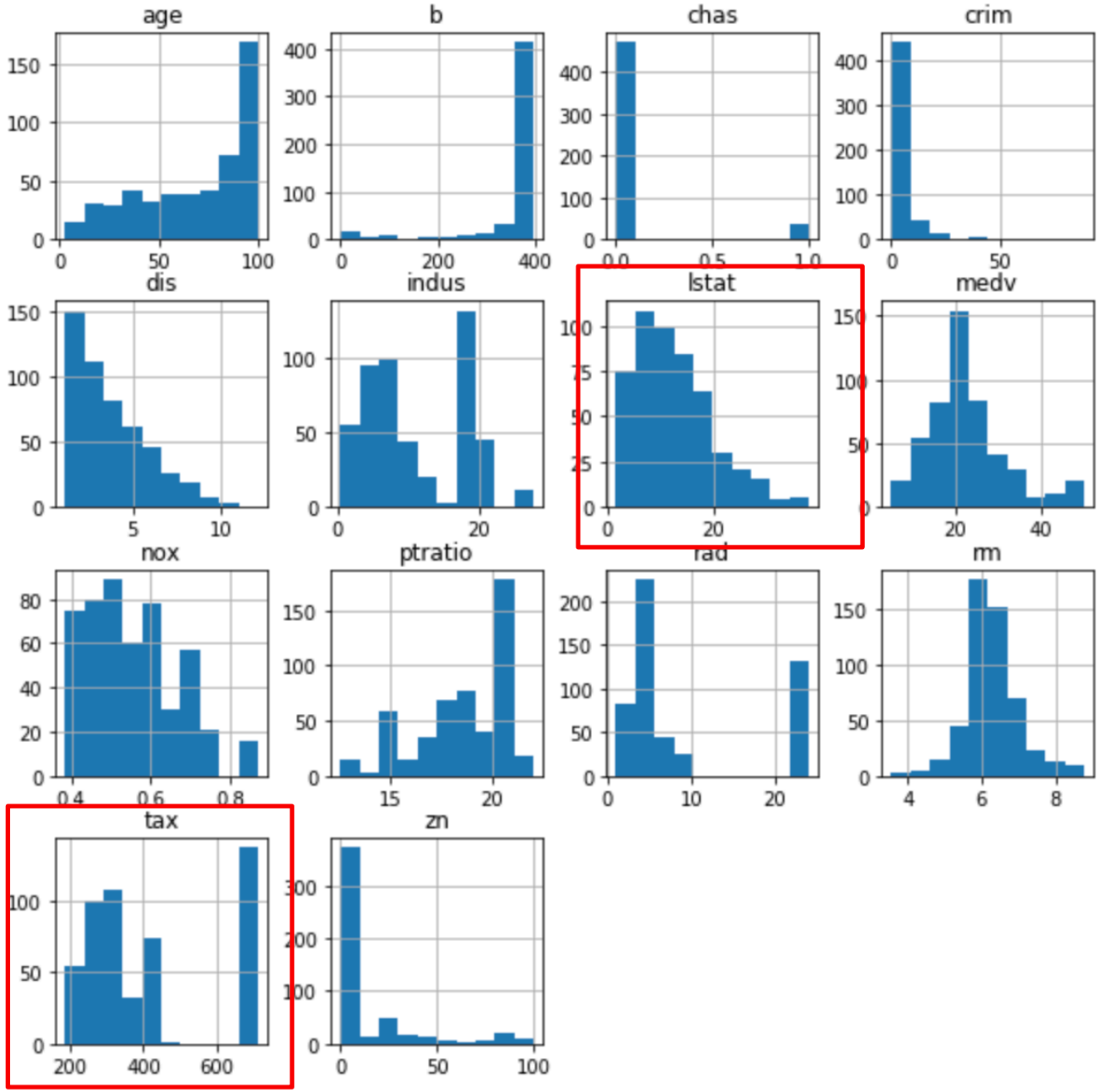
```
hists = boston_df.hist(figsize=(10,10))
```



- CRIM, ZN, AGE 및 B와 같은 변수들은

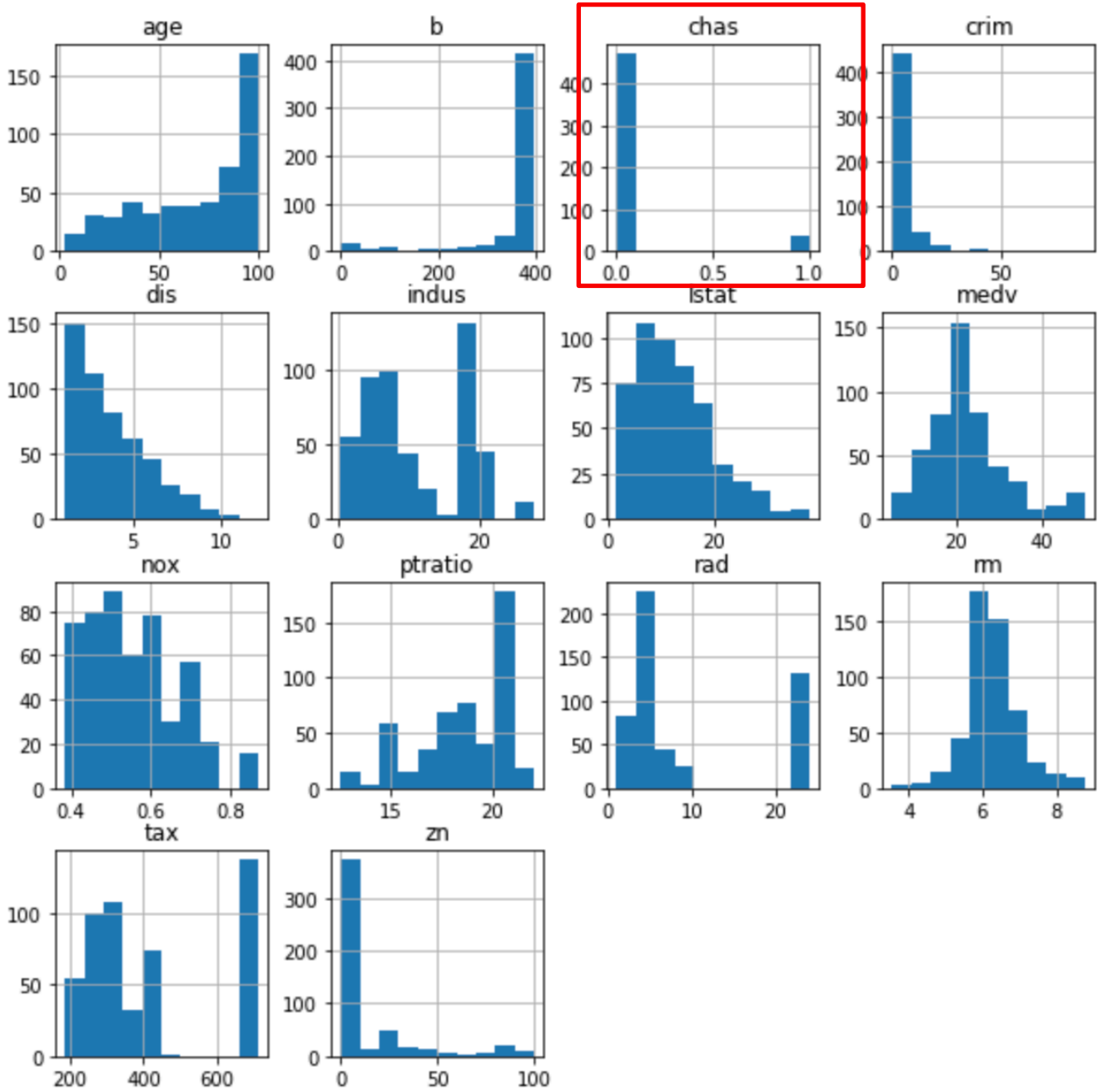
  지수 분포를 따르는 변수

```
hists = boston_df.hist(figsize=(10,10))
```



- CRIM, ZN, AGE 및 B와 같은 변수들은 지수 분포를 따르는 변수
- RAD와 TAX 변수는 이분산 분포 형태

```
hists = boston_df.hist(figsize=(10,10))
```



- CRIM, ZN, AGE 및 B와 같은 변수들은 지수 분포를 따르는 변수
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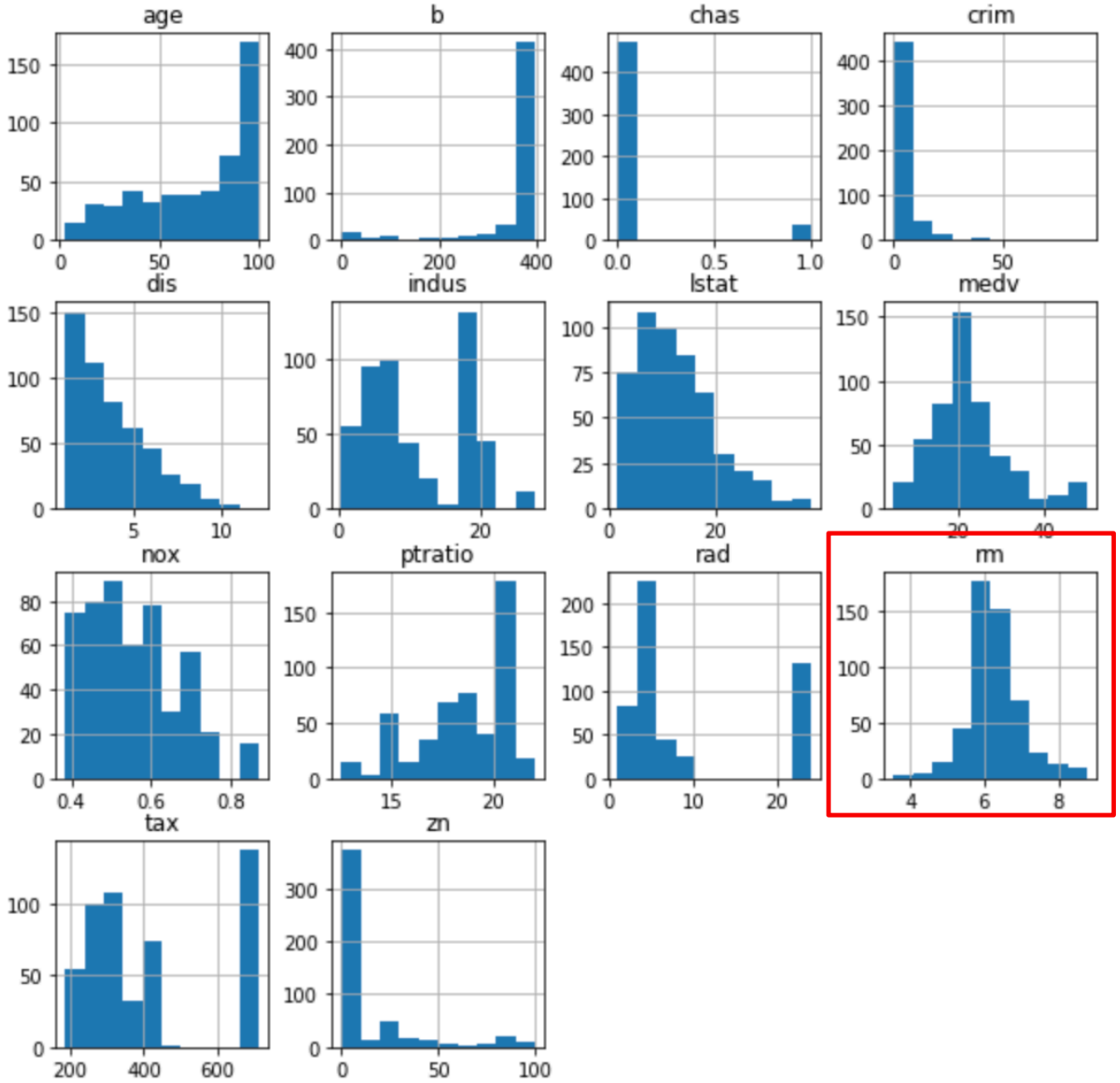
- CHAS는 범주형 변수, 회귀에 적당하지 않음

```
hists = boston_df.hist(figsize=(10,10))
```



- CRIM, ZN, AGE 및 B와 같은 변수들은 지수 분포를 따르는 변수
- RAD와 TAX 변수는 이분산 분포 형태
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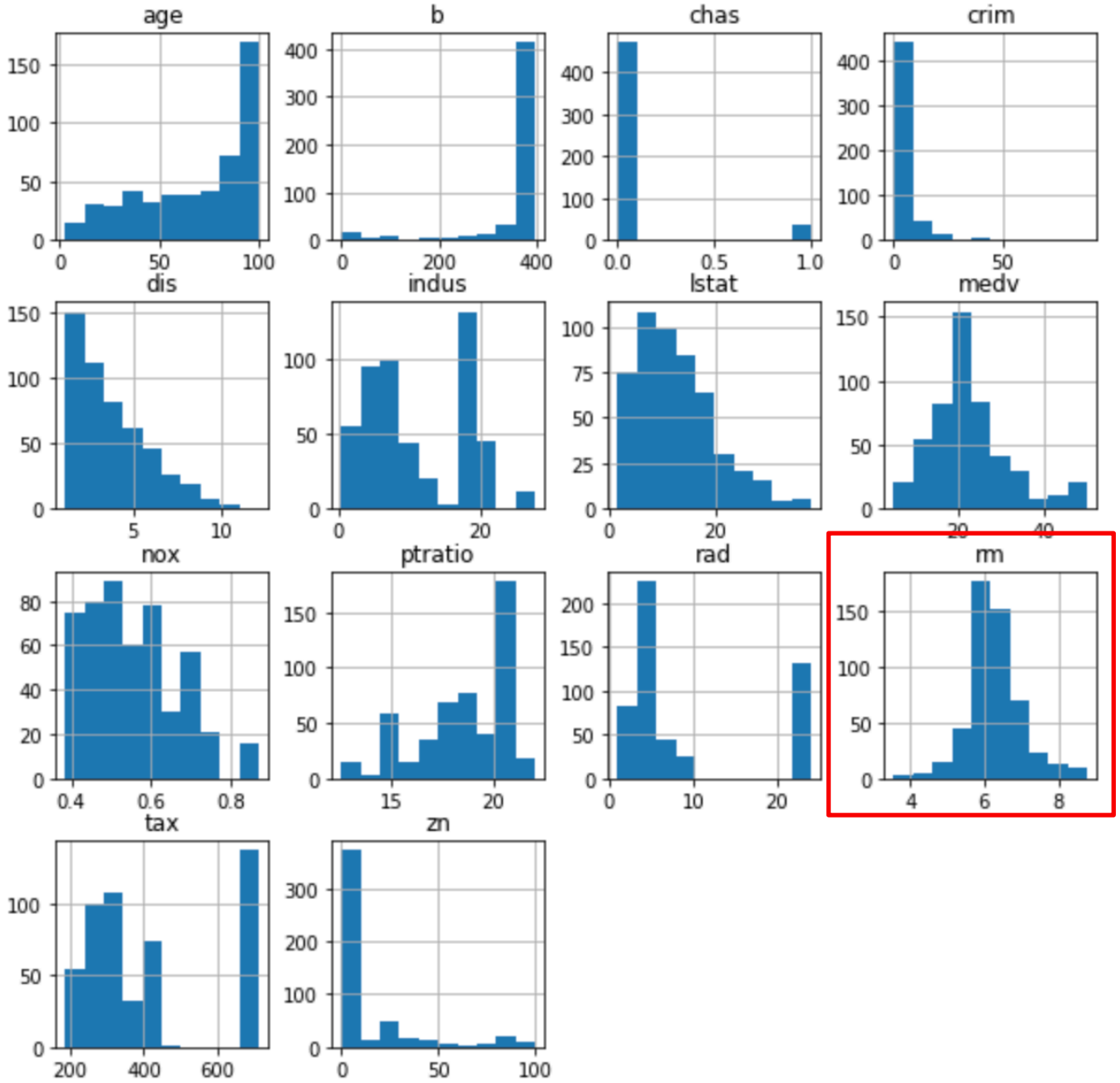
- RM 정규 분포에 가장 가까움

```
hists = boston_df.hist(figsize=(10,10))
```



- CRIM, ZN, AGE 및 B와 같은 변수들은 지수 분포를 따르는 변수
- RAD와 TAX 변수는 이분산 분포 형태
- CHAS는 범주형 변수, 회귀에 적당하지 않음
- RM 정규 분포에 가장 가까움
  - outliner: 8.7, 3.5 제거?

EDA: 상관계수(Correlation coefficient)

$$r = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}}$$

EDA: 상관계수(Correlation coefficient)

$$r = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}}$$

$$R = \begin{pmatrix} r_{x1x1} & r_{x1x2} & \cdots & r_{x1xm} \\ r_{x2x1} & r_{x2x2} & \cdots & r_{x2xm} \\ \vdots & \vdots & & \vdots \\ r_{xnx1} & r_{xnx2} & \cdots & r_{xnxm} \end{pmatrix}$$

$$= \frac{1}{n} \mathbf{Z}^{\mathsf{T}}\mathbf{Z}$$

Correlation matrix 상관관계가 높은 변수 확인

```
corr = boston_df.corr()
corr.style.background_gradient(cmap='coolwarm')
```

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b	lstat
crim	1	-0.200469	0.406583	-0.0558916	0.420972	-0.219247	0.352734	-0.37967	0.625505	0.582764	0.289946	-0.385064	0.455621
zn	-0.200469	1	-0.533828	-0.0426967	-0.516604	0.311991	-0.569537	0.664408	-0.311948	-0.314563	-0.391679	0.17552	-0.412995
indus	0.406583	-0.533828	1	0.062938	0.763651	-0.391676	0.644779	-0.708027	0.595129	0.72076	0.383248	-0.356977	0.6038
chas	-0.0558916	-0.0426967	0.062938	1	0.0912028	0.0912512	0.0865178	-0.0991758	-0.00736824	-0.0355865	-0.121515	0.0487885	-0.0539293
nox	0.420972	-0.516604	0.763651	0.0912028	1	-0.302188	0.73147	-0.76923	0.611441	0.668023	0.188933	-0.380051	0.590879
rm	-0.219247	0.311991	-0.391676	0.0912512	-0.302188	1	-0.240265	0.205246	-0.209847	-0.292048	-0.355501	0.128069	-0.613808
age	0.352734	-0.569537	0.644779	0.0865178	0.73147	-0.240265	1	-0.747881	0.456022	0.506456	0.261515	-0.273534	0.602339
dis	-0.37967	0.664408	-0.708027	-0.0991758	-0.76923	0.205246	-0.747881	1	-0.494588	-0.534432	-0.232471	0.291512	-0.496996
rad	0.625505	-0.311948	0.595129	-0.00736824	0.611441	-0.209847	0.456022	-0.494588	1	0.910228	0.464741	-0.444413	0.488676
tax	0.582764	-0.314563	0.72076	-0.0355865	0.668023	-0.292048	0.506456	-0.534432	0.910228	1	0.460853	-0.441808	0.543993
ptratio	0.289946	-0.391679	0.383248	-0.121515	0.188933	-0.355501	0.261515	-0.232471	0.464741	0.460853	1	-0.177383	0.374044
b	-0.385064	0.17552	-0.356977	0.0487885	-0.380051	0.128069	-0.273534	0.291512	-0.444413	-0.441808	-0.177383	1	-0.366087
lstat	0.455621	-0.412995	0.6038	-0.0539293	0.590879	-0.613808	0.602339	-0.496996	0.488676	0.543993	0.374044	-0.366087	1
medv	-0.388305	0.360445	-0.483725	0.17526	-0.427321	0.69536	-0.376955	0.249929	-0.381626	-0.468536	-0.507787	0.333461	-0.737663

Correlation matrix 상관관계가 높은 변수 확인(LSTAT, PTRATIO, RM, INDUS, TAX, NOX)

```
corr = boston_df.corr()
corr.style.background_gradient(cmap='coolwarm')
```

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b	lstat
crim	1	-0.200469	0.406583	-0.0558916	0.420972	-0.219247	0.352734	-0.37967	0.625505	0.582764	0.289946	-0.385064	0.455621
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chas	-0.0558916	-0.0426967	0.062938	1	0.0912028	0.0912512	0.0865178	-0.0991758	-0.00736824	-0.0355865	-0.121515	0.0487885	-0.0539293
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age	0.352734	-0.569537	0.644779	0.0865178	0.73147	-0.240265	1	-0.747881	0.456022	0.506456	0.261515	-0.273534	0.602339
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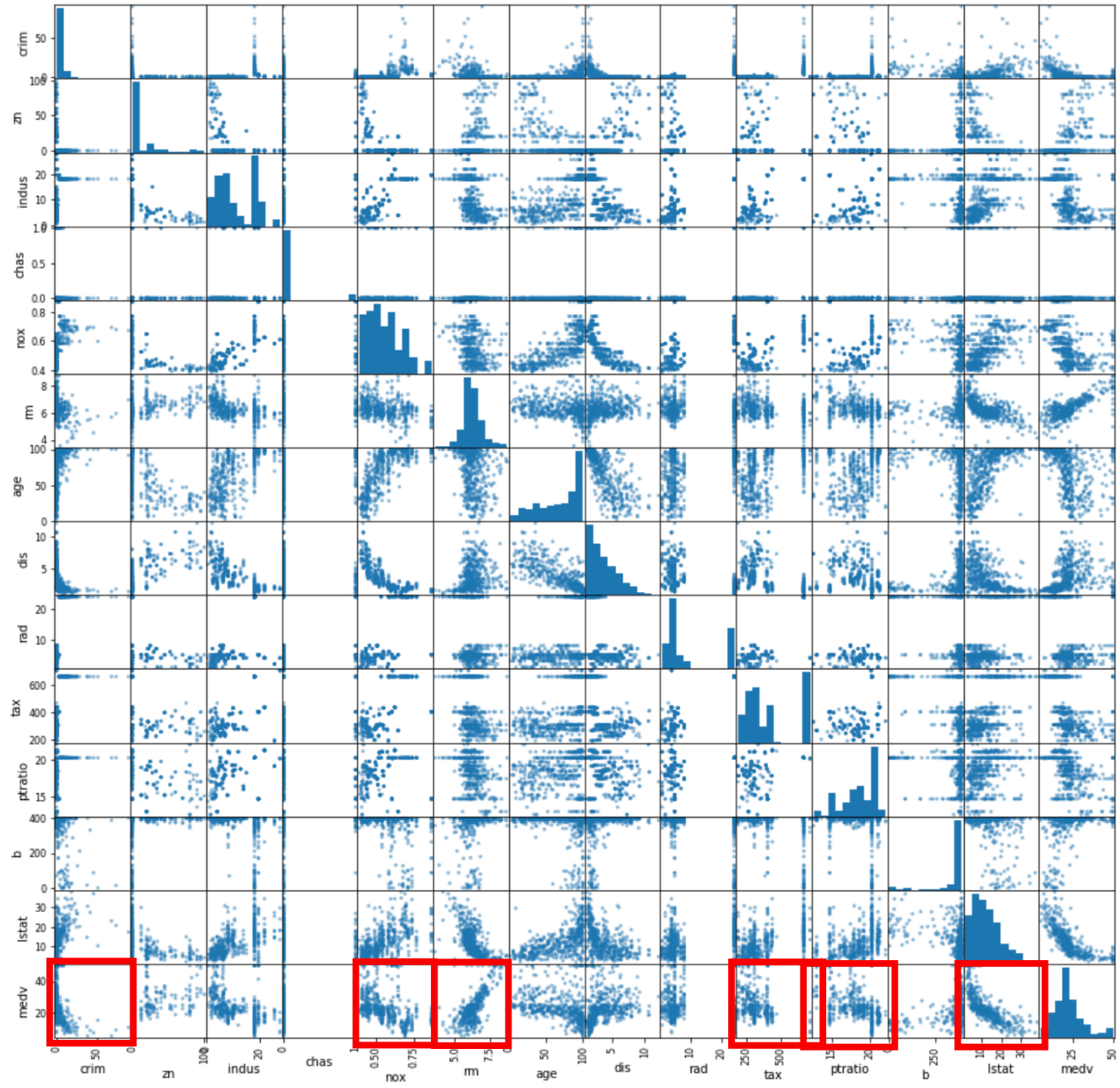
lstat	0.455621	-0.412995	0.6038	-0.0539293	0.590879	-0.613808	0.602339	-0.496996	0.488676	0.543993	0.374044	-0.366087	1
medv	-0.388305	0.360445	-0.483725	0.17526	-0.427321	0.69536	-0.376955	0.249929	-0.381626	-0.468536	-0.507787	0.333461	-0.737663

```
from pandas.plotting import scatter_matrix

scatter_mx=scatter_matrix(boston_df,figsize=(16,16))
```



Feature Selection

- LSTAT
- PTRATIO
- RM
- INDUS
- TAX
- NOX

속성	설명
CRIM	자치시(town) 별 1인당 범죄율
ZN	25,000 평방피트를 초과하는 거주지역의 비율
INDUS	비소매상업지역이 점유하고 있는 토지의 비율
CHAS	찰스강에 대한 더미변수(강의 경계에 위치한 경우는 1, 아니면 0)
NOX	10ppm 당 농축 일산화질소
RM	주택 1가구당 평균 방의 개수
AGE	1940년 이전에 건축된 소유 주택의 비율
DIS	5개의 보스턴 직업센터까지의 접근성 지수
RAD	방사형 도로까지의 접근성 지수
TAX	10,000 달러 당 재산세율
PTRATIO	자치시(town)별 학생/교사 비율
B	1000(Bk-0.63)^2, 여기서 Bk는 자치시 별 흑인의 비율을 말함.
LSTAT	모집단의 하위계층의 비율(%)
MEDV	본인 소유의 주택가격(단위: $1,000)

데이터 분할

```
array = dataset.values
X = array[:,0:6]
Y = array[:,6]
validation_size = 0.20
seed = 7

X_train, X_validation, y_train, y_validation = model_selection.train_test_split(
    X, Y, test_size=validation_size, random_state=seed)
(X_train.shape, X_validation.shape, y_train.shape, y_validation.shape)
```

```
((404, 6), (102, 6), (404,), (102,))
```

Model: Linear Regression

```
from sklearn.linear_model import LinearRegression
from sklearn import metrics

lr = LinearRegression()
lr.fit(X_train, y_train)

y_predict = lr.predict(X_train)
score = metrics.r2_score(y_train, y_predict)
print("training data R2:", score)
```

```
training data R2: 0.7191347800673977
```

```
y_predict = lr.predict(X_validation)
score = metrics.r2_score(y_validation, y_predict)
print("validation data R2:", score)
```

```
validation data R2: 0.4909674625349041
```

Mean Squire Error =

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - t_i)^2$$

R Square =

$$1 - \frac{MSE}{VAR(y)}$$

Solution

$$\hat{y} = x_1 w_1 + x_2 w_2 + \cdots + x_n w_n$$

$$3w_1 + 5w_2 - 4w_3 = 7$$

$$-3w_1 - 2w_2 + 4w_3 = 4$$

$$6w_1 - 1w_2 + 8w_3 = 4$$

Solution: 어떤 솔루션이 가장 좋을까?

$$3w_1 + 5w_2 - 4w_3 = 7$$
$$-3w_1 - 2w_2 + 4w_3 = 4$$
$$6w_1 - 1w_2 + 8w_3 = 4$$

(-1, 2, 0)

(0, 2, 4/3)

(5, 2, 18/4)

Model: Lasso – 선형 회귀의 의미 없는 가중치 제거

```
lasso =  Lasso()
lasso.fit(X_train, y_train)

y_predict = lasso.predict(X_train)
score = metrics.r2_score(y_train, y_predict)
print("training data, Lasso - R2:", score)

y_predict = lasso.predict(X_validation)
score = metrics.r2_score(y_validation, y_predict)
print("training data, Lasso - R2:", score)
```

```
training data, Lasso - R2: 0.6820528235623888
training data, Lasso - R2: 0.5756970763637104
```

$$w = \arg\min_{w} \left(\sum_{i=1}^{N} e_i^2 + \lambda \sum_{j=1}^{M} |w_j| \right)$$

미분시 가중치 항은 상수

Model: Ridge – 선형 회귀의 가중치를 작게

```
ridge =  Ridge()
ridge.fit(X_train, y_train)

y_predict = ridge.predict(X_train)
score = metrics.r2_score(y_train, y_predict)
print("training data, Ridge - R2:", score)

y_predict = ridge.predict(X_validation)
score = metrics.r2_score(y_validation, y_predict)
print("validation data, Ridge - R2:", score)
```

```
training data, Ridge - R2: 0.7190244677684591
validation data, Ridge - R2: 0.49319666826328645
```

$$w = \arg\min_{w} \left(\sum_{i=1}^{N} e_i^2 + \lambda \sum_{j=1}^{M} w_j^2 \right)$$

미분시 가중치 항은 L2 Norm인 Weight 항은 비율이 됨

Model: ElasticNet = Ridge + Lasso

```
from sklearn.linear_model import ElasticNet

en =  ElasticNet()
en.fit(X_train, y_train)

y_predict = en.predict(X_train)
score = metrics.r2_score(y_train, y_predict)
print("training data, ElasticNet - R2:", score)

y_predict = en.predict(X_validation)
score = metrics.r2_score(y_validation, y_predict)
print("validation data, ElasticNet - R2:", score)
```

```
training data, ElasticNet - R2: 0.6565504044092061
validation data, ElasticNet - R2: 0.5906796176638256
```

$$w = \arg\min_{w} \left(\sum_{i=1}^{N} e_i^2 + \lambda_1 \sum_{j=1}^{M} |w_j| + \lambda_2 \sum_{j=1}^{M} w_j^2 \right)$$

Feature Extraction

```
from sklearn.preprocessing import PolynomialFeatures

poly = PolynomialFeatures(degree=2)
poly.fit(X)
x_data = poly.transform(X)

X_train, X_validation, y_train, y_validation = model_selection.train_test_split(
    x_data, Y, test_size=validation_size, random_state=seed)
(X_train.shape, X_validation.shape, y_train.shape, y_validation.shape)
```

```
((404, 28), (102, 28), (404,), (102,))
```

```
lr = LinearRegression()
lr.fit(X_train, y_train)

y_predict = lr.predict(X_train)
score = metrics.r2_score(y_train, y_predict)
print("training data Linear Regression - R2:", score)

y_predict = lr.predict(X_validation)
score = metrics.r2_score(y_validation, y_predict)
print("validation data Linear Regression - R2:", score)
```

```
training data Linear Regression - R2: 0.8748489620171976
validation data Linear Regression - R2: 0.745611172233344
```

Model 검증

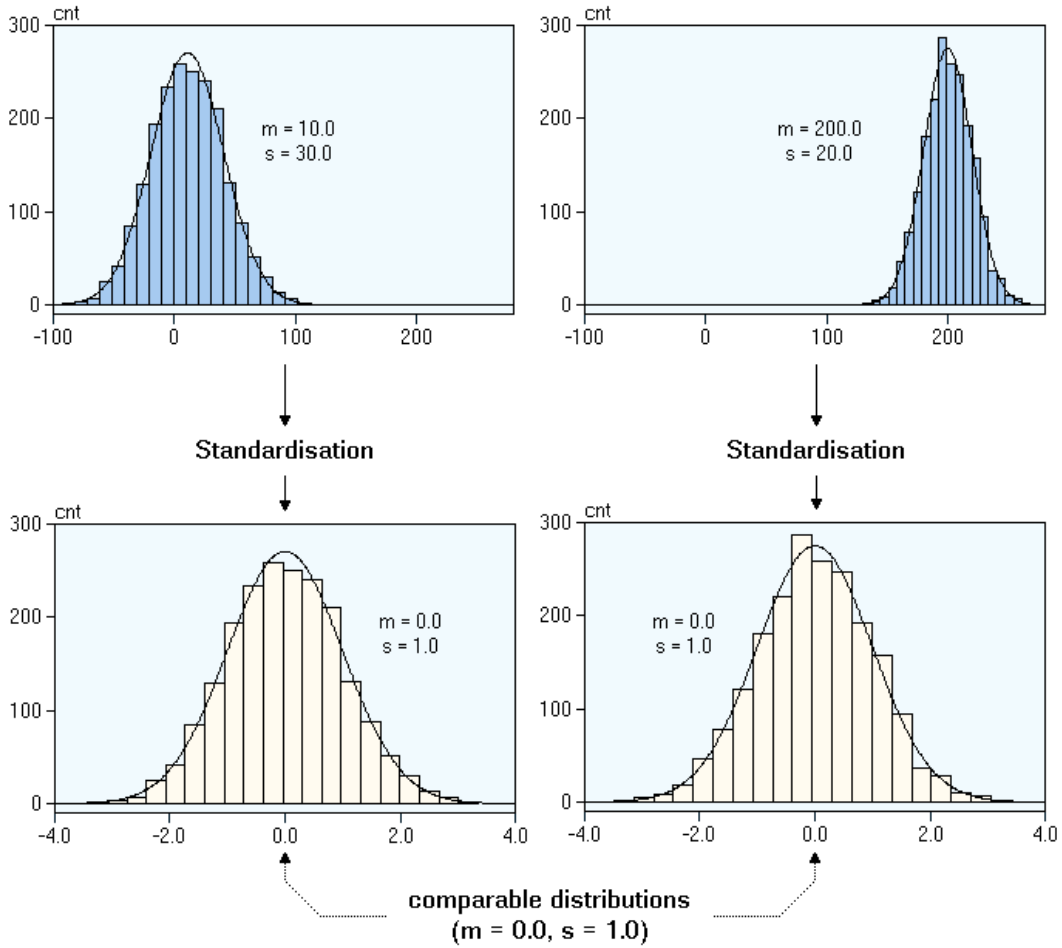
```
seed=35
kfold=KFold(n_splits=10,random_state=seed)
num_folds = 10
```

```
models = []
models.append(('LR', LinearRegression()))
models.append(('LASSO', Lasso()))
models.append(('EN', ElasticNet()))
models.append(('KNN', KNeighborsRegressor()))
models.append(('CART', DecisionTreeRegressor()))
models.append(('SVR', SVR()))
```

```
results = []
names = []
for name, model in models:
    kfold = KFold(n_splits=num_folds, random_state=seed)
    cv_results = cross_val_score(model, X_train, Y_train, cv=kfold, scoring='r2')
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)
```

```
LR: 0.834867 (0.076225)
LASSO: 0.830806 (0.084568)
EN: 0.831369 (0.084819)
KNN: 0.694156 (0.115922)
```

Standardization



$$z = \frac{x_i - \mu}{\sigma}$$

Model 검증: 표준화 데이터

```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
pipelines = []
pipelines.append(('ScaledLR', Pipeline([('Scaler', StandardScaler()),('LR', LinearRegression())])))
pipelines.append(('ScaledLASSO', Pipeline([('Scaler', StandardScaler()),('LASSO', Lasso())])))
pipelines.append(('ScaledEN', Pipeline([('Scaler', StandardScaler()),('EN', ElasticNet())])))
pipelines.append(('ScaledKNN', Pipeline([('Scaler', StandardScaler()),('KNN', KNeighborsRegressor())])))
pipelines.append(('ScaledCART', Pipeline([('Scaler', StandardScaler()),('CART', DecisionTreeRegressor())])))
pipelines.append(('ScaledSVR', Pipeline([('Scaler', StandardScaler()),('SVR', SVR())])))
results = []
names = []
for name, model in pipelines:
    kfold = KFold(n_splits=num_folds, random_state=seed)
    cv_results = cross_val_score(model, X_train, Y_train, cv=kfold, scoring='r2')
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)
```

```
ScaledLR: 0.834189 (0.077067)
ScaledLASSO: 0.727223 (0.064642)
ScaledEN: 0.702851 (0.062363)
ScaledKNN: 0.823836 (0.073393)
ScaledCART: 0.705543 (0.161044)
ScaledSVR: 0.718610 (0.114292)
```

ADW: 마음은 급한데~~(2019.08.20 03:00)

ADW: 상관 관계

```
BEGIN
  DBMS_PREDICTIVE_ANALYTICS.EXPLAIN(
    data_table_name     => 'boston_house',
    explain_column_name => 'MEDV',
    result_table_name   => 'ai_explain_output');
END;

End;
```

```
PL/SQL procedure successfully completed.
```

Took 16 sec. Last updated by OML at August 20 2019, 9:04:25 AM.

```
%sql
SELECT attribute_name, round(explanatory_value,4), rank
   FROM ai_explain_output
   ORDER BY rank, attribute_name;
```

ATTRIBUTE_NAME	ROUND(EXPLANATORY_VALUE,4)	RANK
LSTAT	0.08	1
SEQ	0.0695	2
RM	0.0483	3
INDUS	0.0443	4
NOX	0.0441	5
TAX	0.0347	6
PTRATIO	0.0331	7
CRIM	0.0267	8
RAD	0.017	9

Took 1 sec. Last updated by OML at August 12 2019, 1:20:02 PM.

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b	lstat
crim	1	-0.200469	0.406583	-0.0558916	0.420972	-0.219247	0.352734	-0.37967	0.625505	0.582764	0.289946	-0.385064	0.455621
zn	-0.200469	1	-0.533828	-0.0426967	-0.516604	0.311991	-0.569537	0.664408	-0.311948	-0.314563	-0.391679	0.17552	-0.412995
indus	0.406583	-0.533828	1	0.062938	0.763651	-0.391676	0.644779	-0.708027	0.595129	0.72076	0.383248	-0.356977	0.6038
chas	-0.0558916	-0.0426967	0.062938	1	0.0912028	0.0912512	0.0865178	-0.0991758	-0.00736824	-0.0355865	-0.121515	0.0487885	-0.0539293
nox	0.420972	-0.516604	0.763651	0.0912028	1	-0.302188	0.73147	-0.76923	0.611441	0.668023	0.188933	-0.380051	0.590879
rm	-0.219247	0.311991	-0.391676	0.0912512	-0.302188	1	-0.240265	0.205246	-0.209847	-0.292048	-0.355501	0.128069	-0.613808
age	0.352734	-0.569537	0.644779	0.0865178	0.73147	-0.240265	1	-0.747881	0.456022	0.506456	0.261515	-0.273534	0.602339
dis	-0.37967	0.664408	-0.708027	-0.0991758	-0.76923	0.205246	-0.747881	1	-0.494588	-0.534432	-0.232471	0.291512	-0.496996
rad	0.625505	-0.311948	0.595129	-0.00736824	0.611441	-0.209847	0.456022	-0.494588	1	0.910228	0.464741	-0.444413	0.488676
tax	0.582764	-0.314563	0.72076	-0.0355865	0.668023	-0.292048	0.506456	-0.534432	0.910228	1	0.460853	-0.441808	0.543993
ptratio	0.289946	-0.391679	0.383248	-0.121515	0.188933	-0.355501	0.261515	-0.232471	0.464741	0.460853	1	-0.177383	0.374044
b	-0.385064	0.17552	-0.356977	0.0487885	-0.380051	0.128069	-0.273534	0.291512	-0.444413	-0.441808	-0.177383	1	-0.366087
lstat	0.455621	-0.412995	0.6038	-0.0539293	0.590879	-0.613808	0.602339	-0.496996	0.488676	0.543993	0.374044	-0.366087	1
medv	-0.388305	0.360445	-0.483725	0.17526	-0.427321	0.69536	0.376955	0.249929	-0.381626	-0.468536	0.507787	0.333461	-0.737663

LSTAT, PTRATIO, RM, INDUS, TAX, NOX

ADW: 데이터 분할

FINISHED

```
%script
/*  Split the Data into N1_TRAIN_DATA and N1_TEST_DATA  */
BEGIN
EXECUTE IMMEDIATE 'CREATE OR REPLACE VIEW  AS SELECT * FROM boston_house SAMPLE (75) SEED
    (1)';
DBMS_OUTPUT.PUT_LINE ('Created N1_TRAIN_DATA');
EXECUTE IMMEDIATE 'CREATE OR REPLACE VIEW N1_TEST_DATA AS SELECT * FROM boston_house
    MINUS SELECT * FROM N1_TRAIN_DATA';
DBMS_OUTPUT.PUT_LINE ('Created N1_TEST_DATA');
END;
/
```

```
Created N1_TRAIN_DATA
Created N1_TEST_DATA
PL/SQL procedure successfully completed.
---------------------------
```

Took 0 sec. Last updated by OML at August 05 2019, 4:32:45 PM. (c

Sklearn Code: 학습 / 검증 데이터 분할

```
array = dataset.values
X = array[:,0:6]
Y = array[:,6]
validation_size = 0.20
seed = 7

X_train, X_validation, y_train, y_validation = model_selection.train_test_split(
    X, Y, test_size=validation_size, random_state=seed)
(X_train.shape, X_validation.shape, y_train.shape, y_validation.shape)
```

```
((404, 6), (102, 6), (404,), (102,))
```

ADW: 모델 설정

FINISHED

```
%sql
CREATE TABLE glmr_BH_settings (
  setting_name  VARCHAR2(30),
  setting_value VARCHAR2(4000));
```

```
Updated 0 row(s).
```

Took 0 sec. Last updated by OML at August 12 2019, 1:30:22 PM.

FINISHED

```
%script
BEGIN
/* Populate settings table  */
  INSERT INTO glmr_BH_settings (setting_name, setting_value) VALUES     (dbms_data_mining.algo_name,
      dbms_data_mining.algo_generalized_linear_model);
  -- output row diagnostic statistics into a table named GLMC_SH_SAMPLE_DIAG
  INSERT INTO  glmr_BH_settings (setting_name, setting_value) VALUES     (dbms_data_mining
      .glms_diagnostics_table_name, 'glmr_BH_diag');
  INSERT INTO  glmr_BH_settings (setting_name, setting_value) VALUES     (dbms_data_mining.prep_auto
      , dbms_data_mining.prep_auto_on);
  -- turn on feature selection
  INSERT INTO  glmr_BH_settings (setting_name, setting_value) VALUES      (dbms_data_mining
      .glms_ftr_selection,     dbms_data_mining.glms_ftr_selection_enable);
  -- turn on feature generation
  INSERT INTO  glmr_BH_settings (setting_name, setting_value) VALUES     (dbms_data_mining
      .glms_ftr_generation,     dbms_data_mining.glms_ftr_generation_enable);
  --특정 컬럼 가중치를 줄때
  --INSERT INTO  glmr_BH_settings (setting_name, setting_value) VALUES     (dbms_data_mining
      .odms_row_weight_column_name , '컬럼명' ) -- 숫자타입 컬럼 만 가능함
  --없는 값 처리에 대한 옵션 , 기본 값은 평균
  --INSERT INTO  glmr_BH_settings (setting_name, setting_value) VALUES     (dbms_data_mining
      .odms_missing_value_treatment,  dbms_data_mining.odms_missing_value_delete_row);
  -- 리지 적용 L2 노름 적용
  --INSERT INTO  glmr_BH_settings (setting_name, setting_value) VALUES     (dbms_data_mining
      .glms_ridge_regression, dbms_data_mining.glms_ridge_reg_enable);
  --INSERT INTO  glmr_BH_settings (setting_name, setting_value) VALUES     (dbms_data_mining
      .GLMS_VIF_FOR_RIDGE, dbms_data_mining.GLMS_VIF_RIDGE_ENABLE);
```

class sklearn.cluster.KMeans(

n_clusters=8, init='kmeans++', n_init=10, max_iter=300, tol=0.0001, precompute_distances='auto', verbose=0, random_state=None, copy_x=True, n_jobs=None, algorithm='auto')

ADW: 모델 생성

```
%script

declare
  v_xlst dbms_data_mining_transform.TRANSFORM_LIST;

BEGIN
  DBMS_DATA_MINING.CREATE_MODEL(
    model_name          => 'GLMR_BH_Regr',
    mining_function     => dbms_data_mining.regression,
    data_table_name     => 'N1_TRAIN_DATA',
    case_id_column_name => 'SEQ',
    target_column_name  => 'MEDV',
    settings_table_name => 'glmr_BH_settings',
    xform_list          => v_xlst);
END;

PL/SQL procedure successfully completed.
```

```
lr = LinearRegression()
lr.fit(X_train, y_train)

y_predict = lr.predict(X_train)
score = metrics.r2_score(y_train, y_predict)
print("training data Linear Regression - R2:", score)

y_predict = lr.predict(X_validation)
score = metrics.r2_score(y_validation, y_predict)
print("validation data Linear Regression - R2:", score)
```

ADW: 모델 평가

```
%sql
select name, numeric_value, string_value from DM$VGGLMR_BH_Regr
  ORDER BY name;
```

FINISHED

NAME	NUMERIC_VALUE	STRING_VALUE
MODEL_F_P_VALUE	0	
MODEL_MEAN_SQUARE	2012.2375015438884	
MODEL_SUM_SQUARES	28171.325021614437	
NUM_PARAMS	15	
NUM_ROWS	367	
ROOT_MEAN_SQ	3.417560090198168	
R_SQ	0.87264773489594027	
SBIC	975.29759537945347	
VALID_COVARIANCE_MATRIX		YES

ADW: Feature Engineering

```
INSERT INTO  glmr_BH_settings (setting_name, setting_value) VALUES     (dbms_data_mining.prep_auto
    , dbms_data_mining.prep_auto_on);
-- turn on feature selection
INSERT INTO  glmr_BH_settings (setting_name, setting_value) VALUES      (dbms_data_mining
    .glms_ftr_selection,     dbms_data_mining.glms_ftr_selection_enable);
```

```
%sql
SELECT attribute_name,feature_expression, coefficient, p_value
  FROM DM$VDGLMR_BH_Regr
  ORDER BY feature_expression;
```

FINISHED

ATTRIBUTE_NAME	FEATURE_EXPRESSION	COEFFICIENT	P_VALUE
	AGE*AGE*AGE	-6.873611091362193E-6	0.00727047040992834
	B	0.028442919184370644	4.475777150931976E-9
	DIS*DIS	-0.03636830108959206	0.0013293549343274607
	INDUS*RAD	0.010358390945203608	0.020787048494195028
	LSTAT*AGE*B	-1.319535441934602	
	LSTAT*CRIM	-0.005710785805384	
	LSTAT*LSTAT	0.0392951760019034	
	LSTAT*TAX	-0.003005106640054	
	RM	17.612007304396727	

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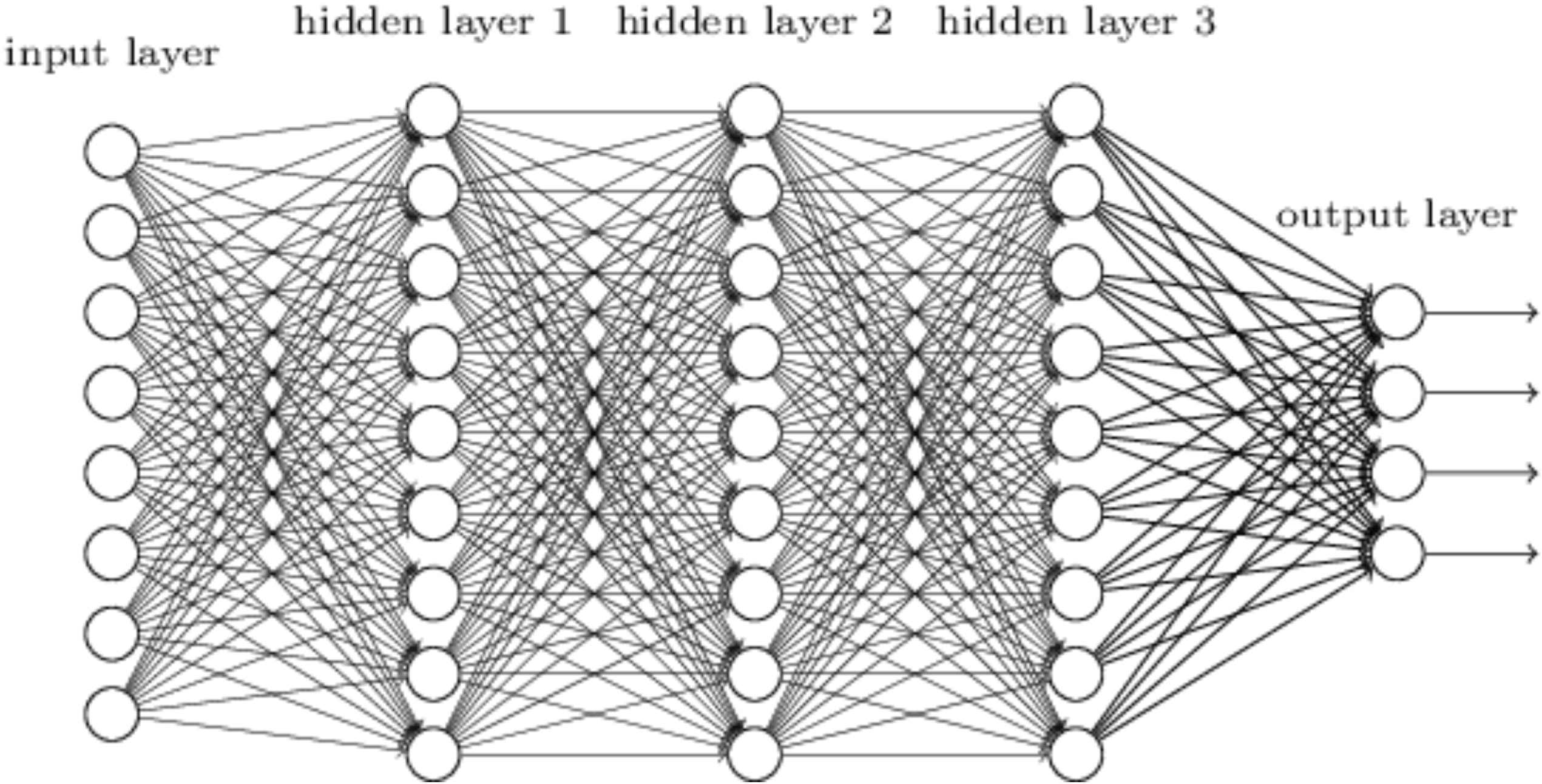
Feature Extraction with Sklearn

```
from sklearn.preprocessing import PolynomialFeatures

poly = PolynomialFeatures(degree=2)
poly.fit(X)
x_data = poly.transform(X)

X_train, X_validation, y_train, y_validation = model_selection.train_test_split(
    x_data, Y, test_size=validation_size, random_state=seed)
(X_train.shape, X_validation.shape, y_train.shape, y_validation.shape)
```

```
((404, 28), (102, 28), (404,), (102,))
```



pytorch_linear_regression_BHP

파일 수정 보기 삽입 런타임 도구 도움말

댓글 공유 태완

+ 코드 + 텍스트 다시 연결 수정 가능

목차 코드 스니펫 파일

Filter code snippets

- Adding form fields
- Camera Capture
- Cross-output communication
- display.Javascript to execute JavaScript f...
- Downloading files or importing data from...
- Downloading files to your local file system
- Evaluate a Javascript expression from Py...

Adding form fields 삽입

Forms example

Forms support multiple types of fields with type checking including sliders, date pickers, input fields, dropdown menus, and dropdown menus that allow input.

Drive Mount

```
[ ] from google.colab import drive
    drive.mount('/gdrive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client

Enter your authorization code:
··········
Mounted at /gdrive
Drive already mounted at /gdrive; to attempt to forcibly remount, call drive.
```

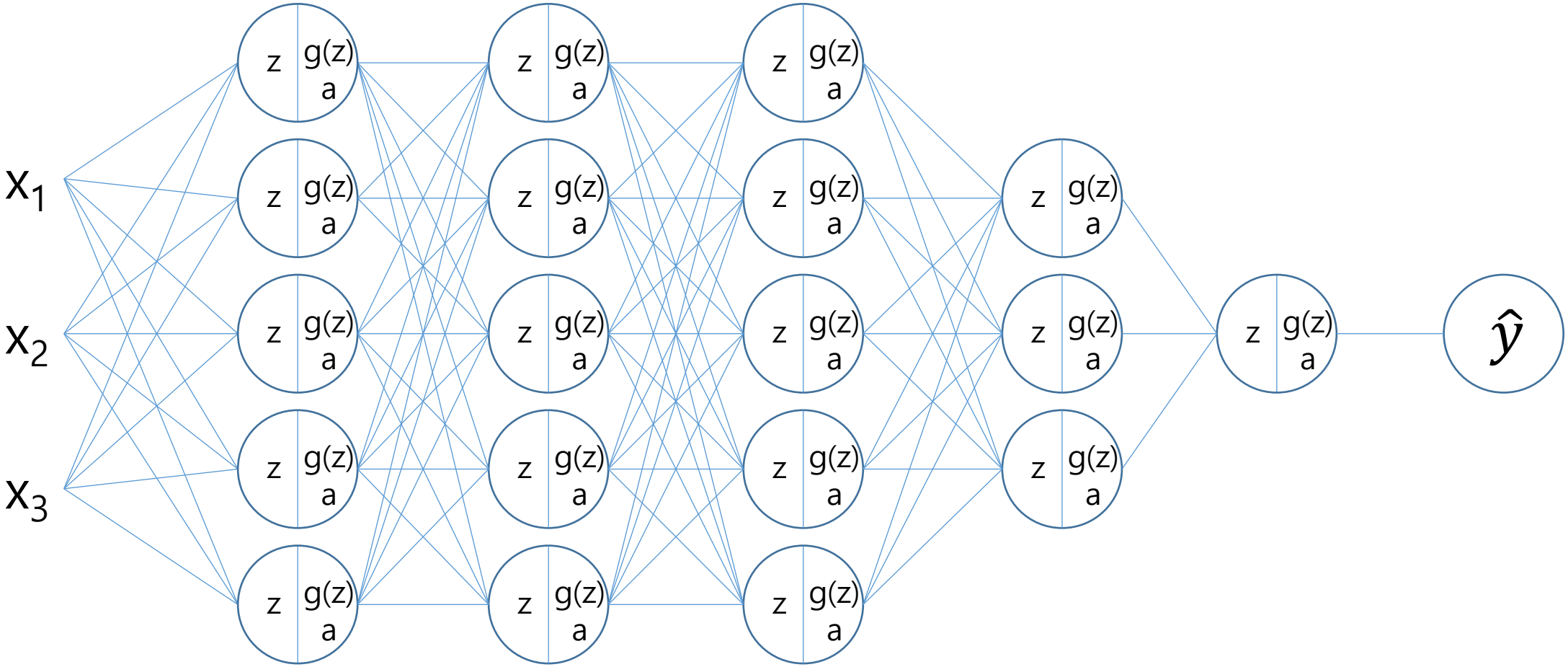
```
[ ] import pandas as pd
    import numpy as np
    from sklearn.model_selection  import train_test_split
    from sklearn import preprocessing
```

```
[ ] boston_df = pd.read_csv("/gdrive/My Drive/boston_house_price.csv")
```

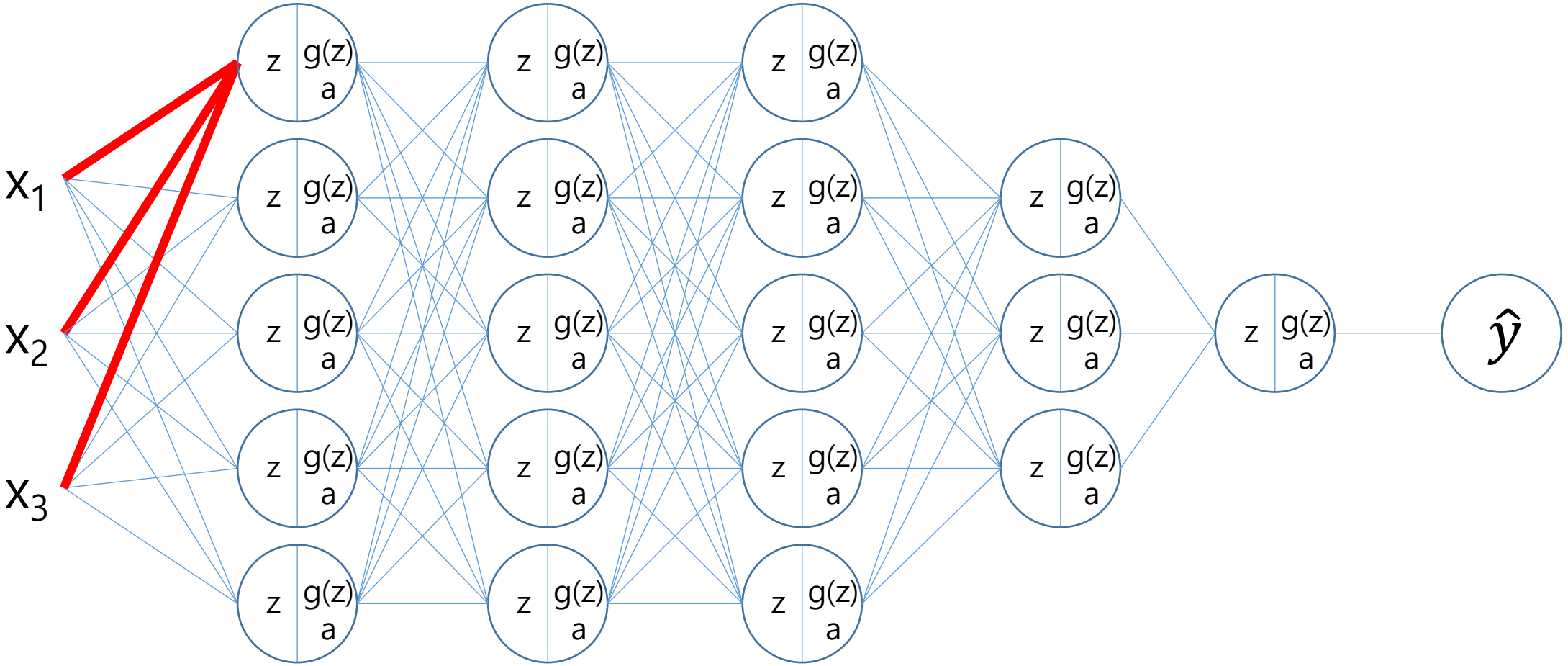
```
[ ] boston_df.head()
```

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90

Deep Learning: Linear Regression



Deep Learning: Linear Regression

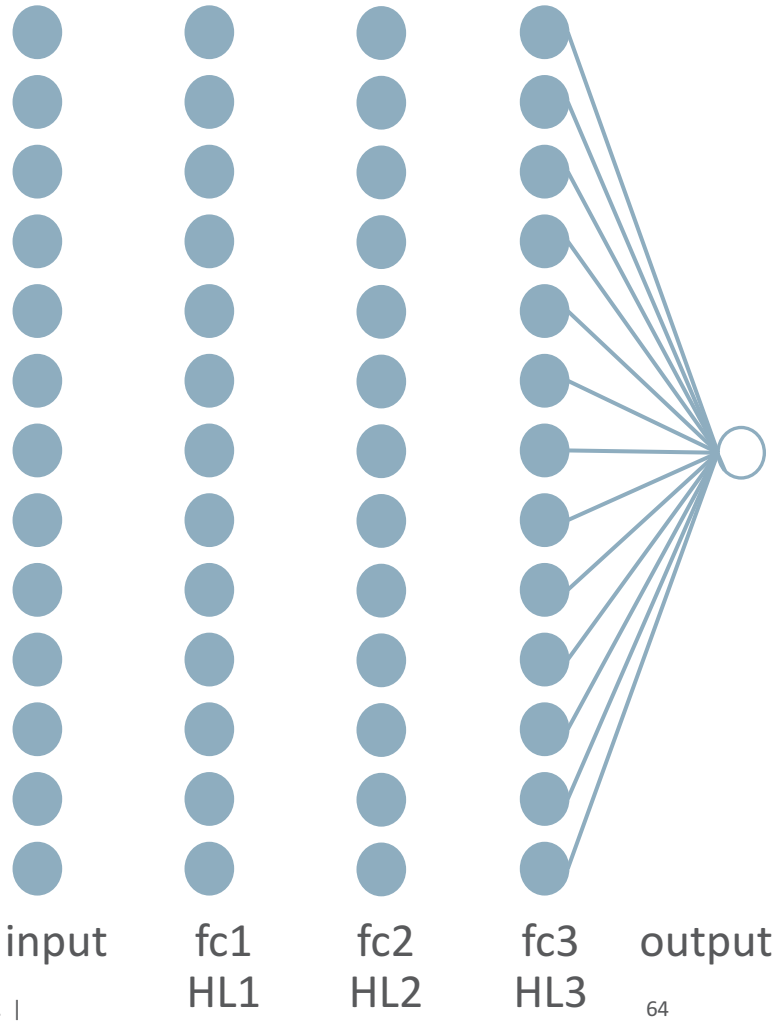


Neural Network Model for Boston House Pricing

```
import torch
import torch.nn as nn
import torch.nn.functional as F

class Regression_NN(nn.Module):
    def __init__(self):
        super().__init__()
        self.fc1 = nn.Linear(13, 13)
        self.fc2 = nn.Linear(13, 13)
        self.fc3 = nn.Linear(13, 1)

        self.dropout = nn.Dropout(p=0.1)


    def forward(self, x):
        x = self.dropout(F.relu(self.fc1(x)))
        x = self.dropout(F.relu(self.fc2(x)))
        #x = F.relu(self.fc1(x))
        #x = F.relu(self.fc2(x))
        x = self.fc3(x)

        return x
```

```
[31] net
```

```
Regression_NN(
  (fc1): Linear(in_features=13, out_features=13, bias=True)
  (fc2): Linear(in_features=13, out_features=13, bias=True)
  (fc3): Linear(in_features=13, out_features=1, bias=True)
  (dropout): Dropout(p=0.1)
)
```



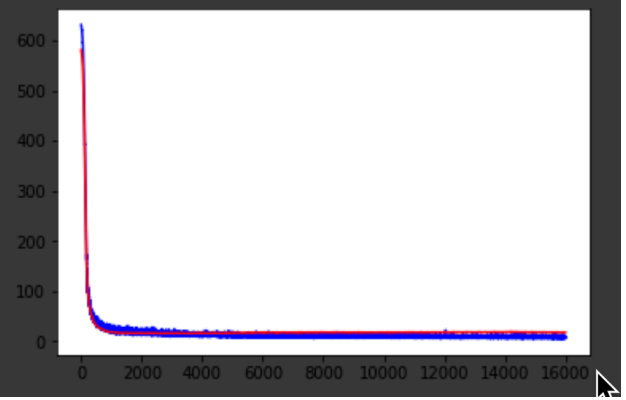
Neural Network Model for Boston House Pricing

```
[35] from sklearn.utils import shuffle
     from torch.autograd import Variable


     batch_size = 50
     num_epochs = 16000
     learning_rate = 0.01

     running_loss = 0.0

     train_errors = []
     test_errors = []


     for epoch in range(num_epochs):
         net.train()
         X_train, y_train = shuffle(X_train, y_train)
         inputs = Variable(torch.FloatTensor(X_train))
         labels = Variable(torch.FloatTensor(y_train))
         optimizer.zero_grad()

         outputs = net.forward(inputs)
         loss = criterion(outputs, torch.unsqueeze(labels,dim=1))
         loss.backward()
         optimizer.step()

         train_errors.append(loss.item())

         if epoch%2000 == 0:
           print('Epoch {}'.format(epoch+1), "loss: ",loss.item())

         net.eval()
         test_inputs = Variable(torch.FloatTensor(X_test))
         test_labels = Variable(torch.FloatTensor(y_test))
         test_output = net.forward(test_inputs)
         test_loss = criterion(test_output, torch.unsqueeze(test_labels,dim=1))
         test_errors.append(test_loss.item())
```

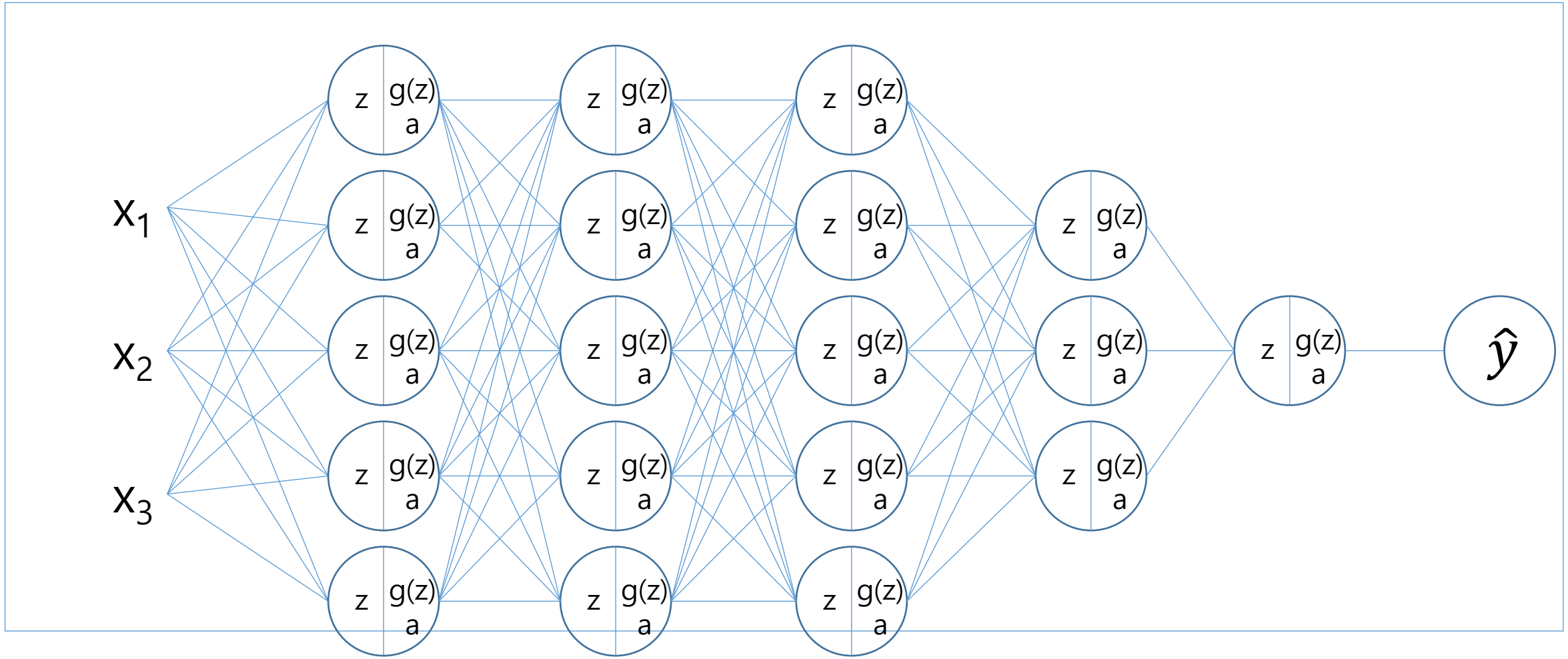
```
Epoch 1 loss:  630.86083984375
Epoch 2001 loss:  14.677943229675293
Epoch 4001 loss:  14.323848724365234
Epoch 6001 loss:  13.816299438476562
Epoch 8001 loss:  8.914133071899414
Epoch 10001 loss:  8.742273330688477
Epoch 12001 loss:  9.113798141479492
Epoch 14001 loss:  8.90151309967041
```

```
[36] import matplotlib.pyplot as plt
     plt.plot(train_errors, 'b-')
     plt.plot(test_errors, 'r-')
```

```
[<matplotlib.lines.Line2D at 0x7fd3c5359358>]
```

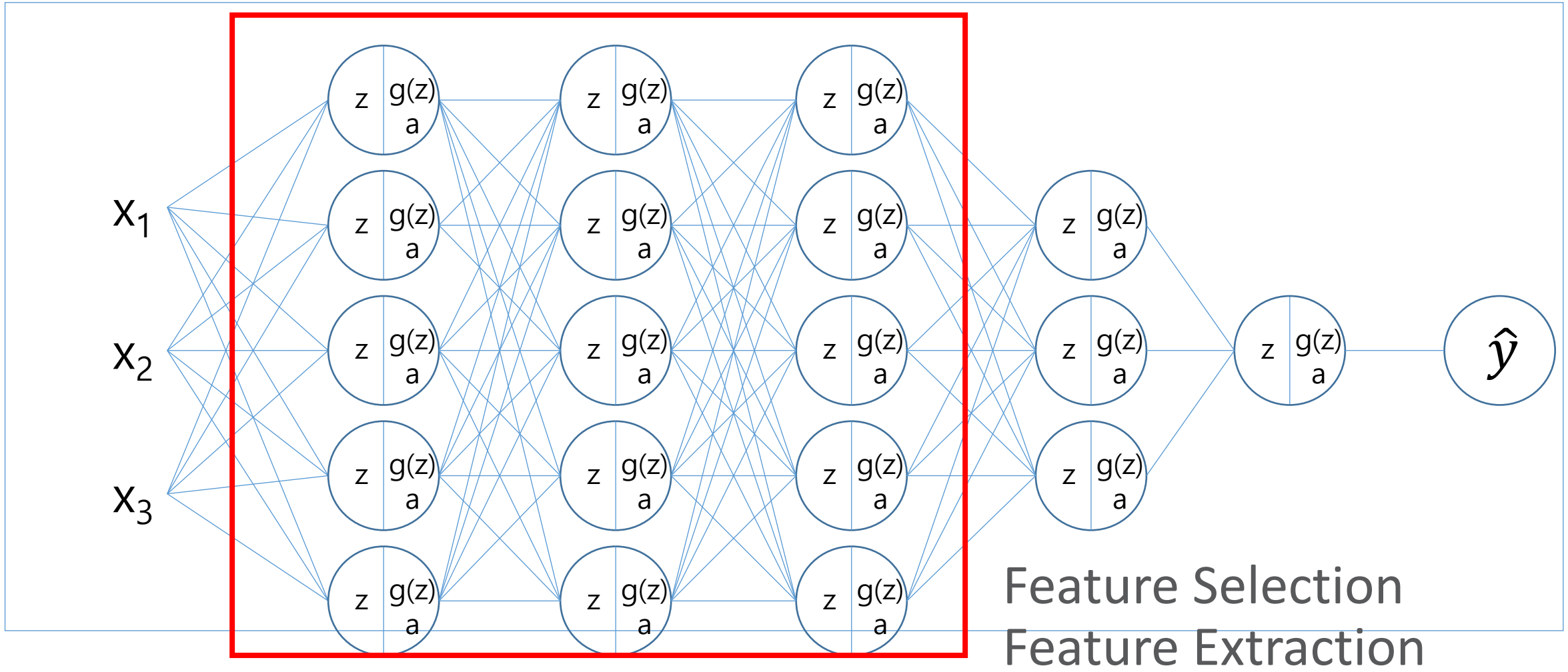


Deep Learning: Linear Regression



https://colah.github.io/posts/2014-03-NN-Manifolds-Topology/

Deep Learning: Linear Regression



https://colah.github.io/posts/2014-03-NN-Manifolds-Topology/

사실은....

```
[ ]  import pandas as pd
     from sklearn.metrics import r2_score
     net.eval()
     X = Variable(torch.FloatTensor(X_train))
     result = net(X)
     pred=result.data[:,0].numpy()
     print(len(pred),len(y_train))
     r2_score(pred,y_train)
```

```
151 151
0.9595044639121458
```

```
[ ]  X = Variable(torch.FloatTensor(X_test))
     result = net(X)
     pred=result.data[:,0].numpy()
     print(len(pred),len(y_test))
     r2_score(pred,y_test)
```

```
355 355
0.7053947564371497
```

Linear Regression ➔ Linear Classification

벡터화

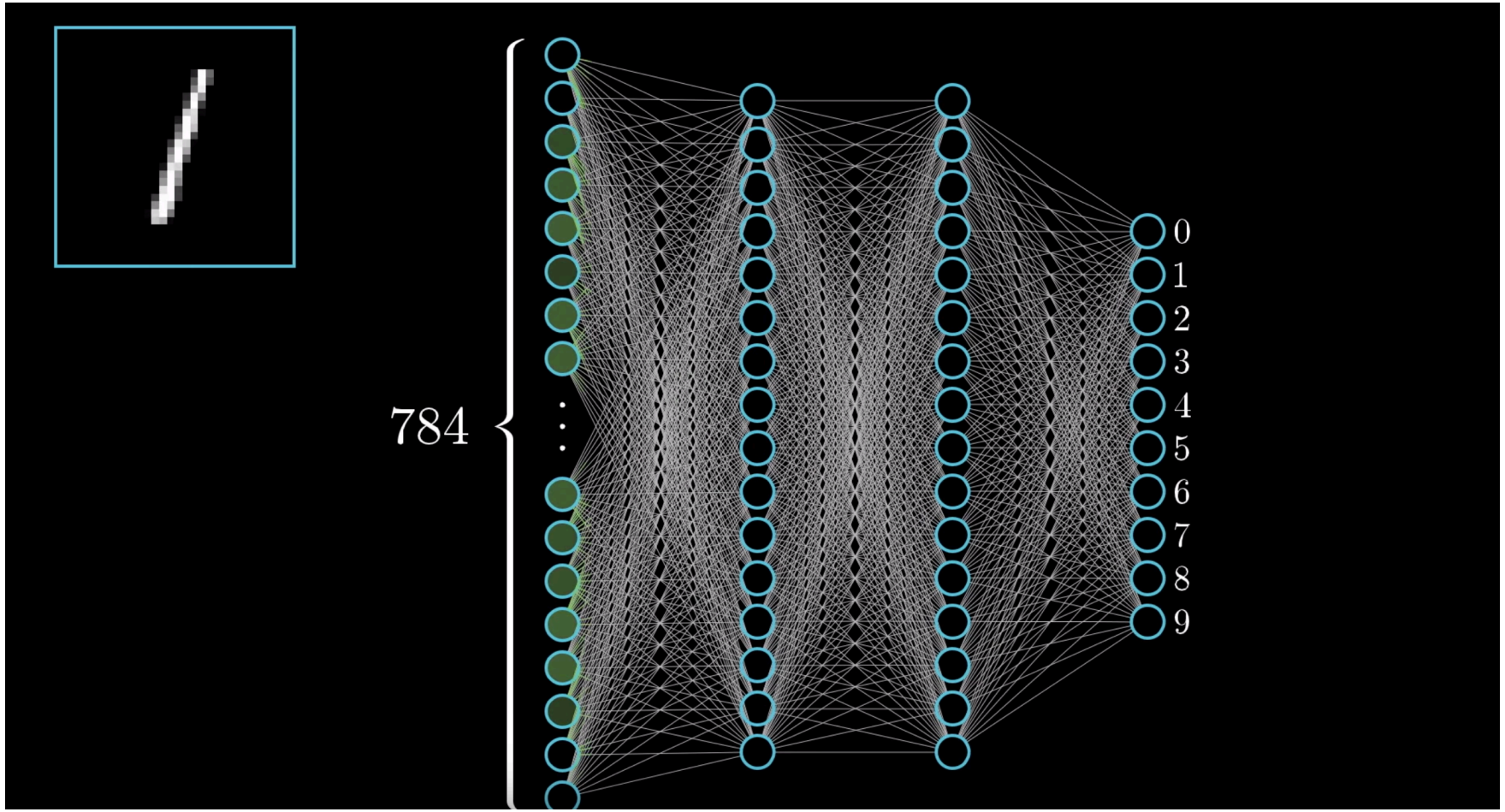
선형변환

비선형 변환

.....

선형변환

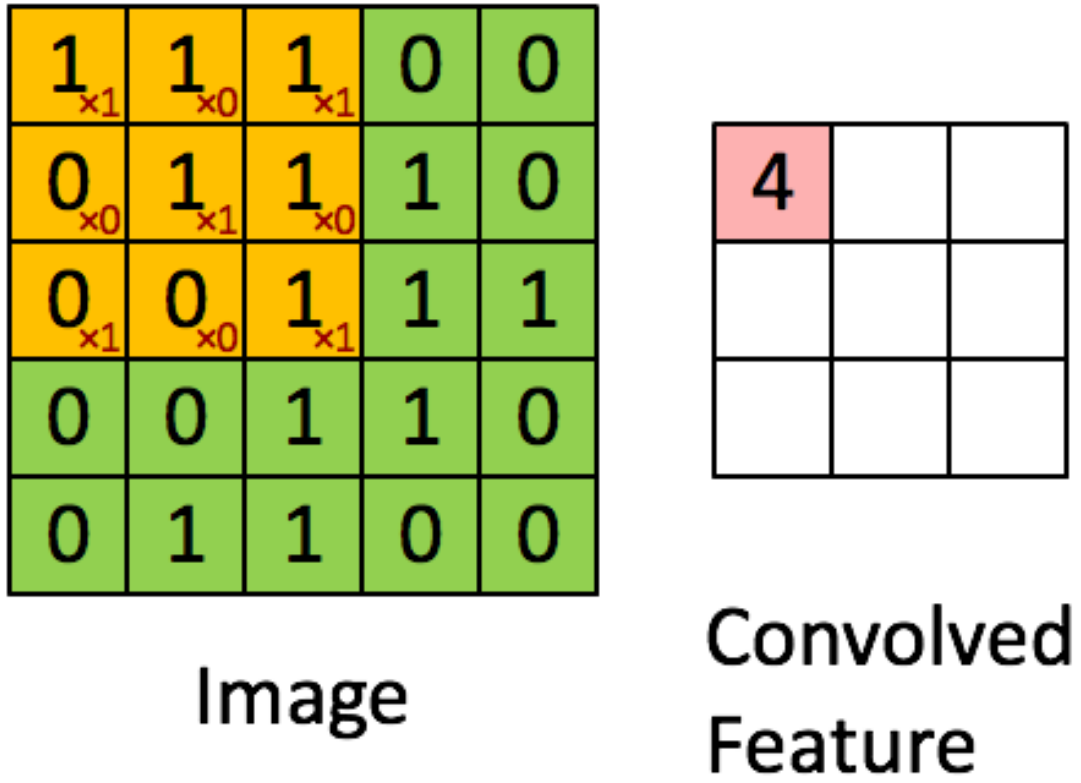
Softmax



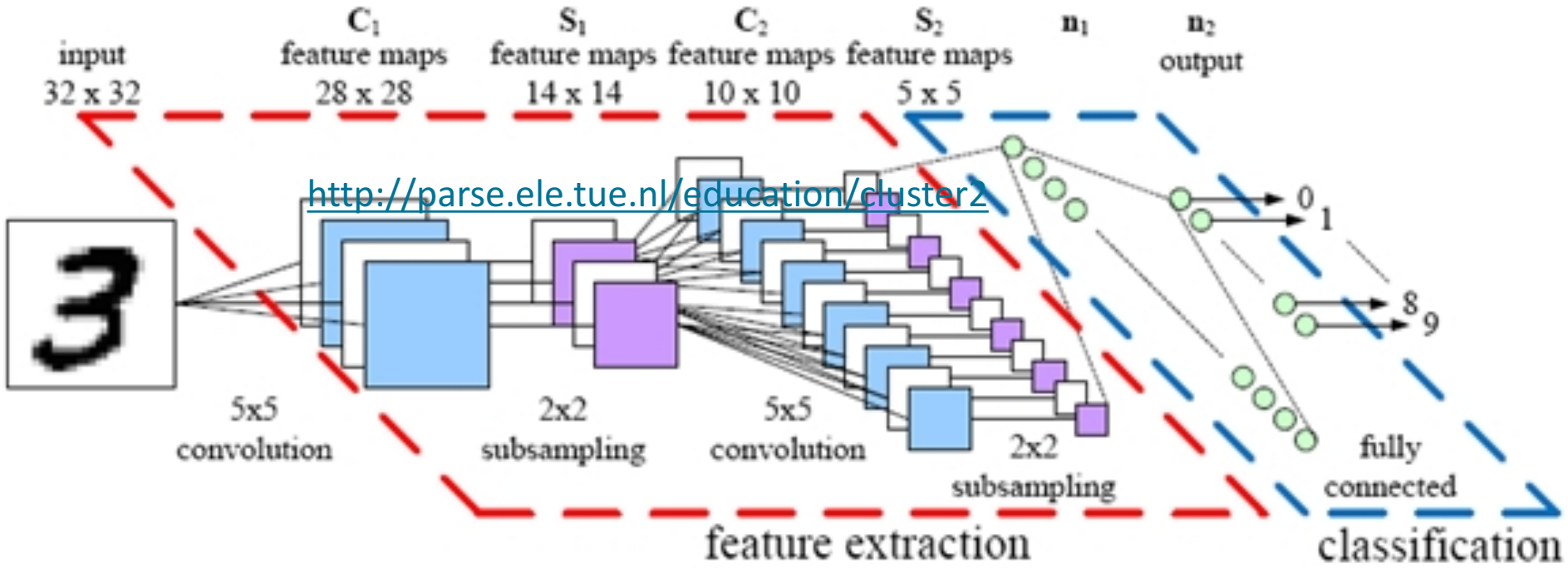
https://www.youtube.com/watch?v=aircAruvnKk

$$Likelihood = \prod_{n=1}^{N} {y_n}^{t_n}(1-y_n)^{1-t_n}$$

공간 데이터 보존: CNN



공간 데이터 보존: CNN

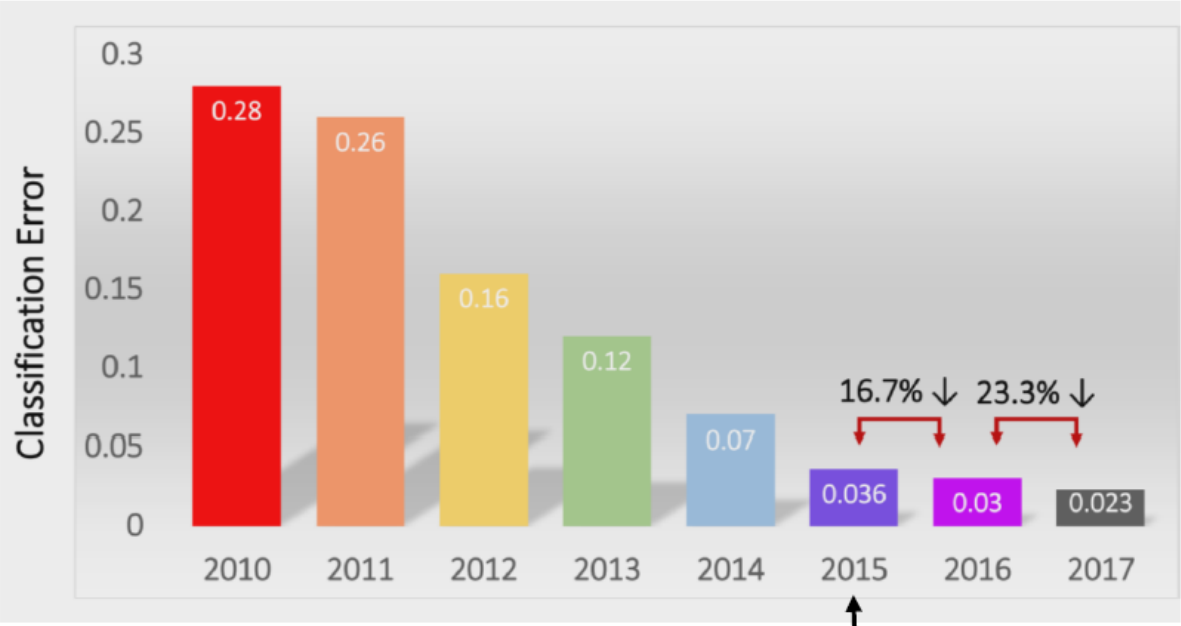


http://parse.ele.tue.nl/education/cluster2

http://parse.ele.tue.nl/education/cluster2

Image Data

ImageNet

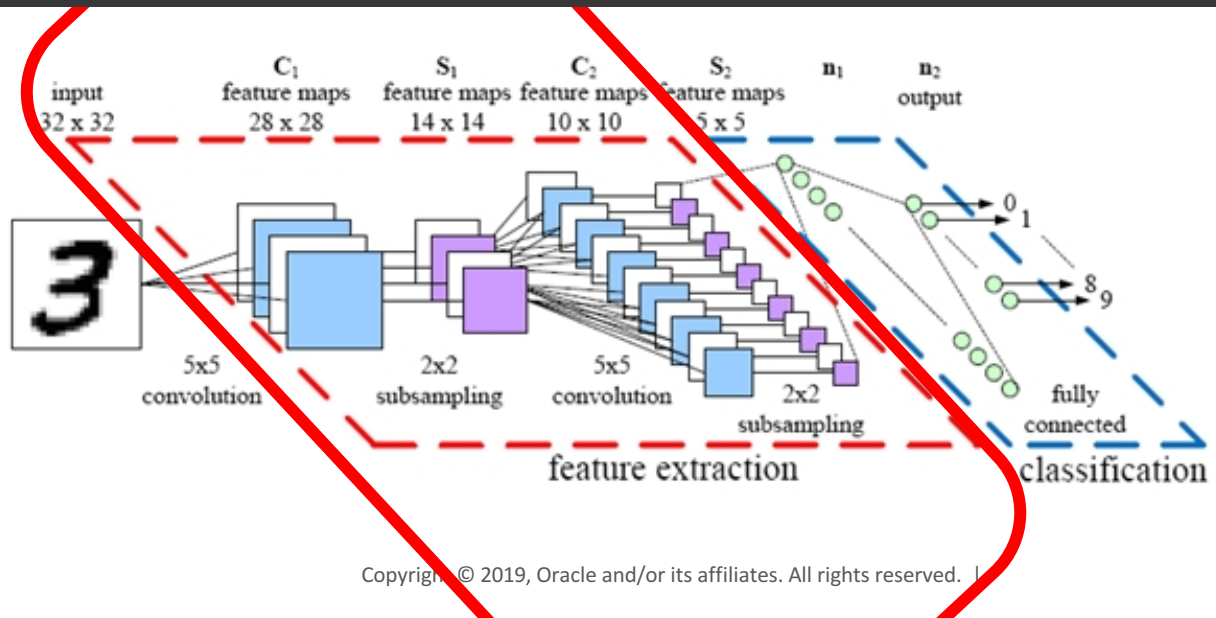


- **AlexNet (2012): First CNN (15.4%)**
  - 8 layers
  - 61 million parameters
- **ZFNet (2013): 15.4% to 11.2%**
  - 8 layers
  - More filters. Denser stride.
- **VGGNet (2014): 11.2% to 7.3%**
  - Beautifully uniform:
    3x3 conv, stride 1, pad 1, 2x2 max pool
  - 16 layers
  - 138 million parameters
- **GoogLeNet (2014): 11.2% to 6.7%**
  - Inception modules
  - 22 layers
  - 5 million parameters
    (throw away fully connected layers)
- **ResNet (2015): 6.7% to 3.57%**
  - More layers = better performance
  - 152 layers
- **CUImage (2016): 3.57% to 2.99%**
  - Ensemble of 6 models
- **SENet (2017): 2.99% to 2.251%**
  - Squeeze and excitation block: network is allowed to adaptively adjust the weighting of each feature map in the convolutional block.

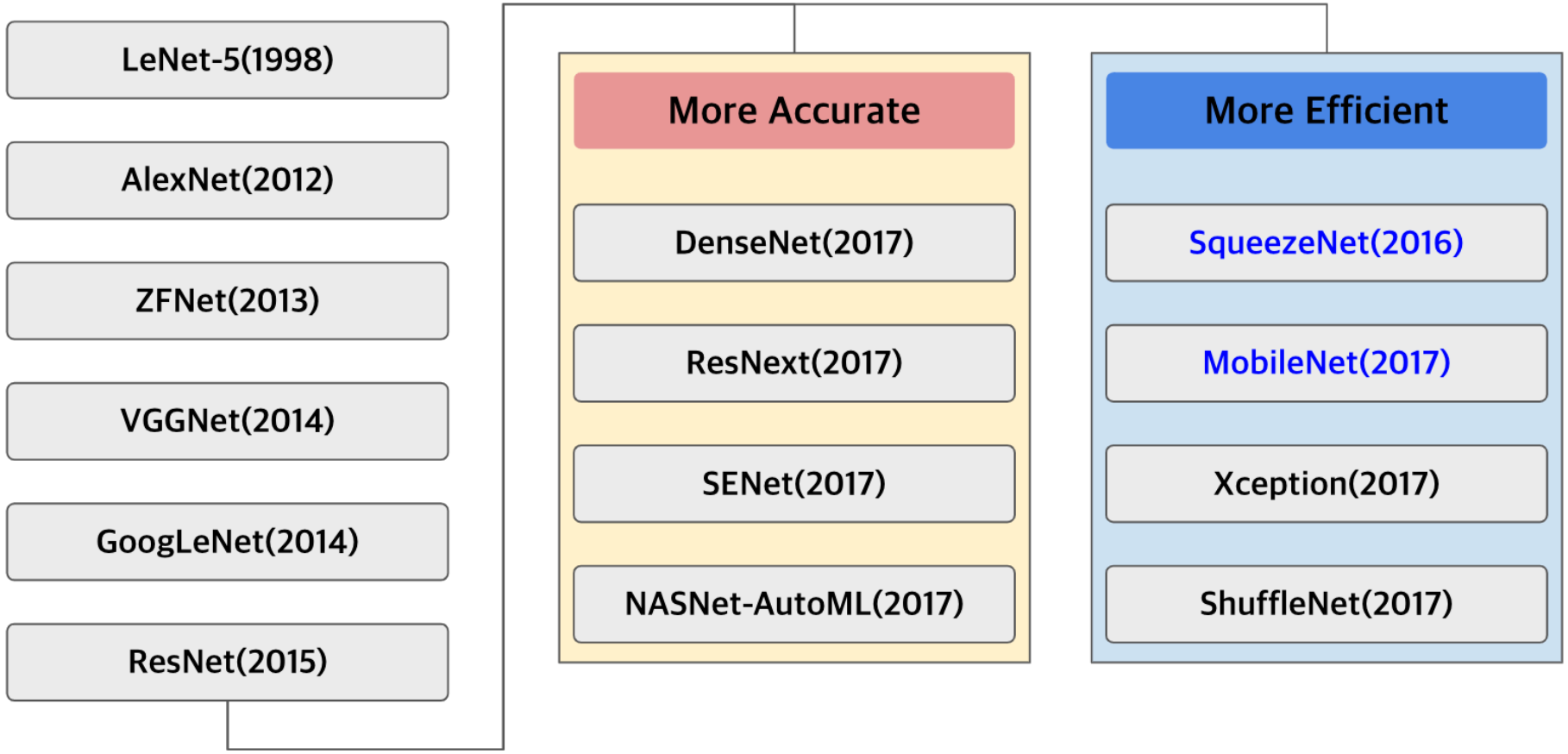
전이학습: Transfer Learning

```
[18] model_ft = models.resnet18(pretrained=True)
     num_ftrs = model_ft.fc.in_features
     model_ft.fc = nn.Linear(num_ftrs, 2)

     if torch.cuda.is_available():
         model_ft = model_ft.cuda()
```

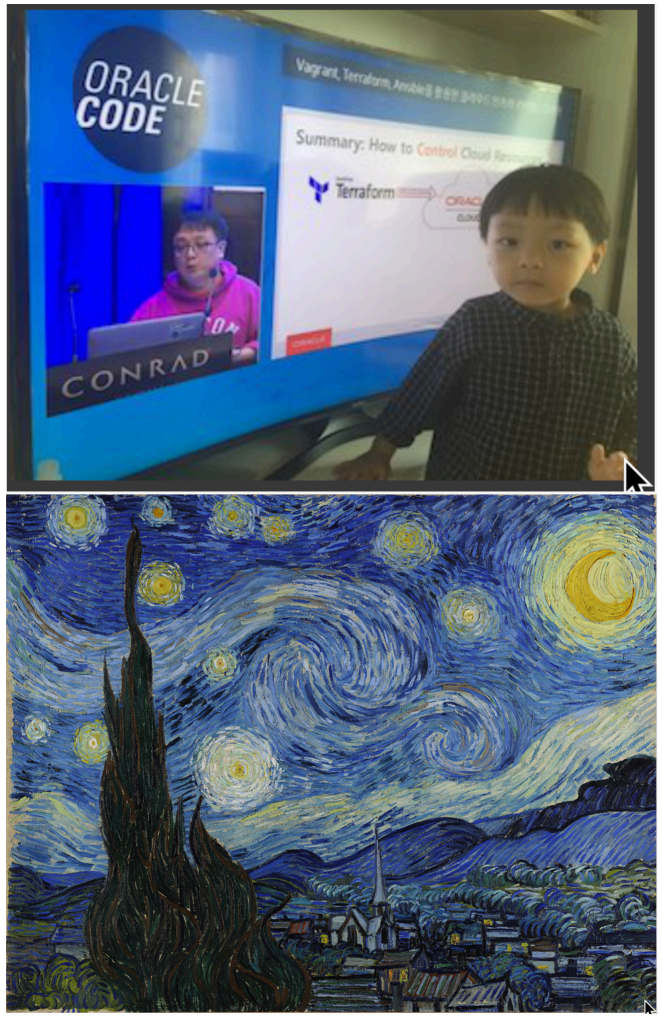
```
Downloading: "https://download.pytorch.org/models/resnet18-5c106cde.pth" to
100%|██████████| 46827520/46827520 [00:00<00:00, 72851894.93it/s]
```



비전 기술 흐름



Style Transfer



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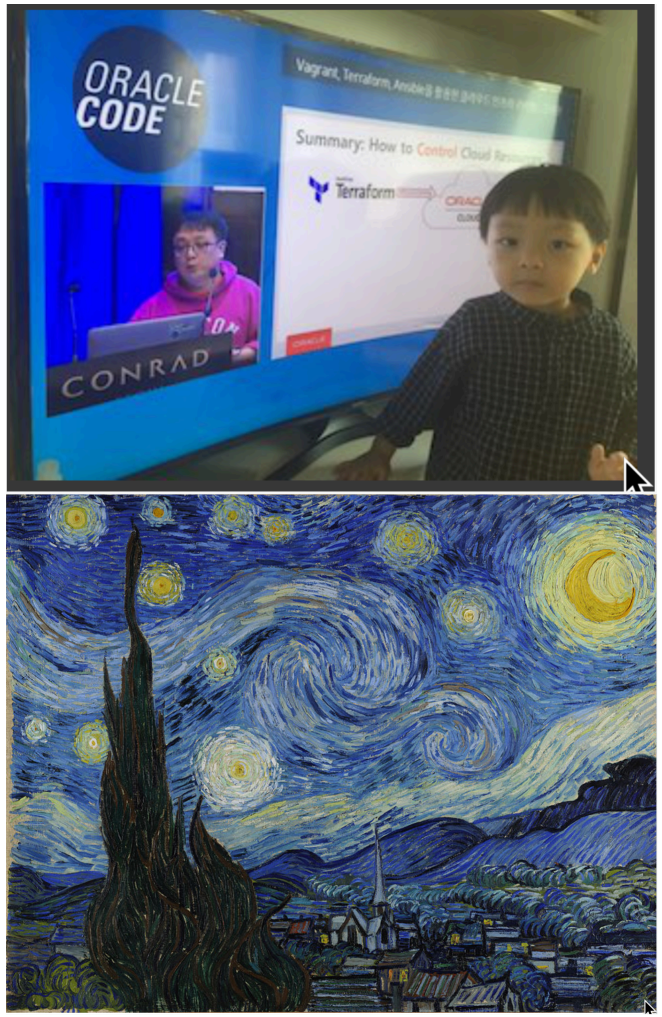

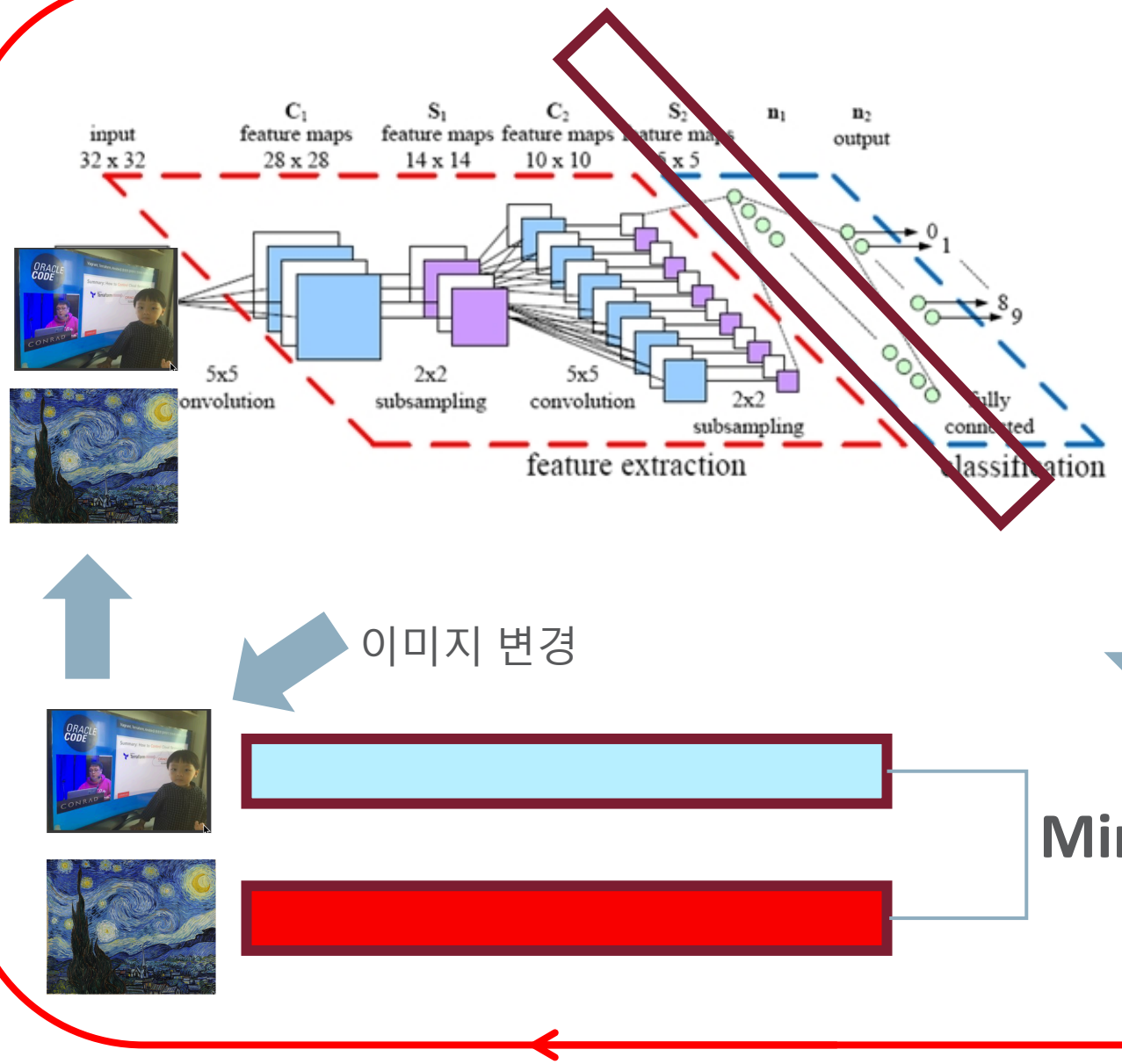

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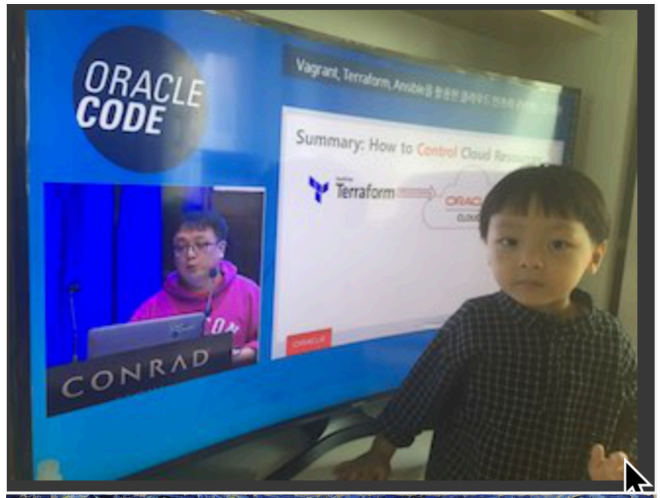

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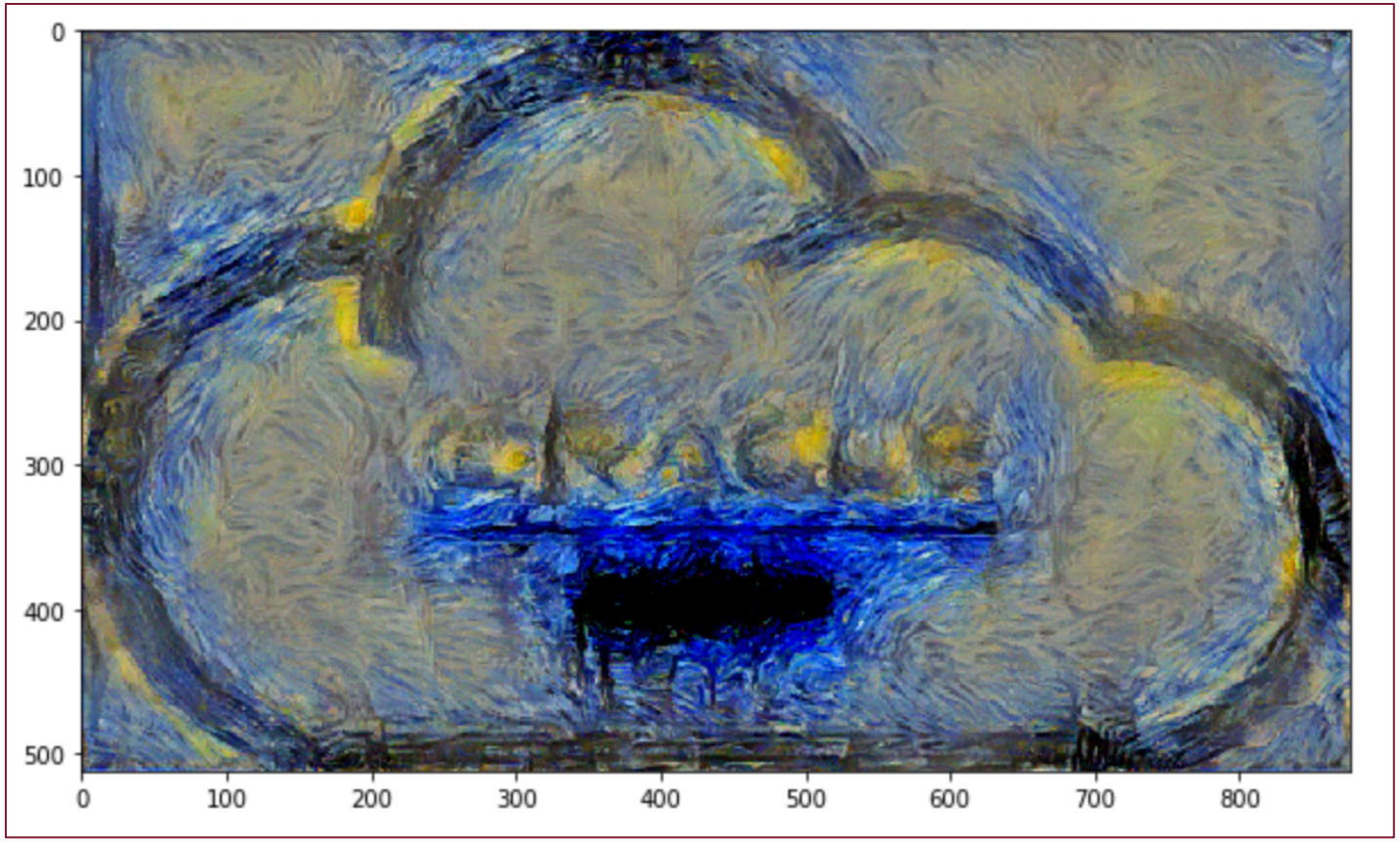


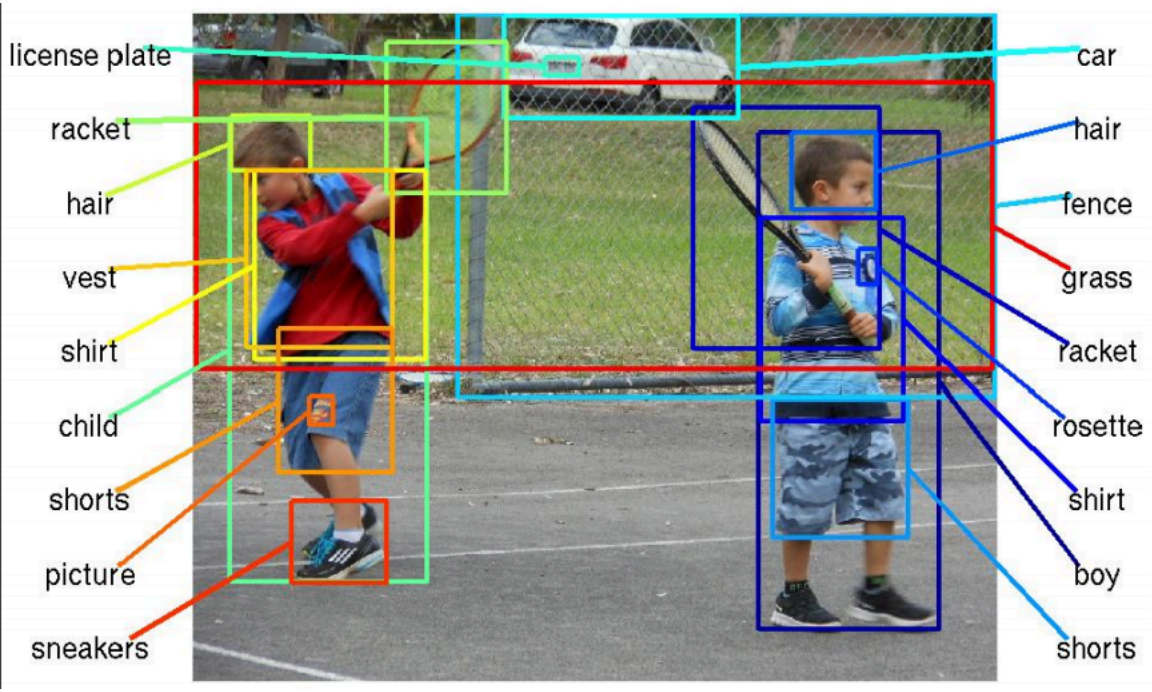
Object Recognition & Caption

"man in black shirt is playing guitar."

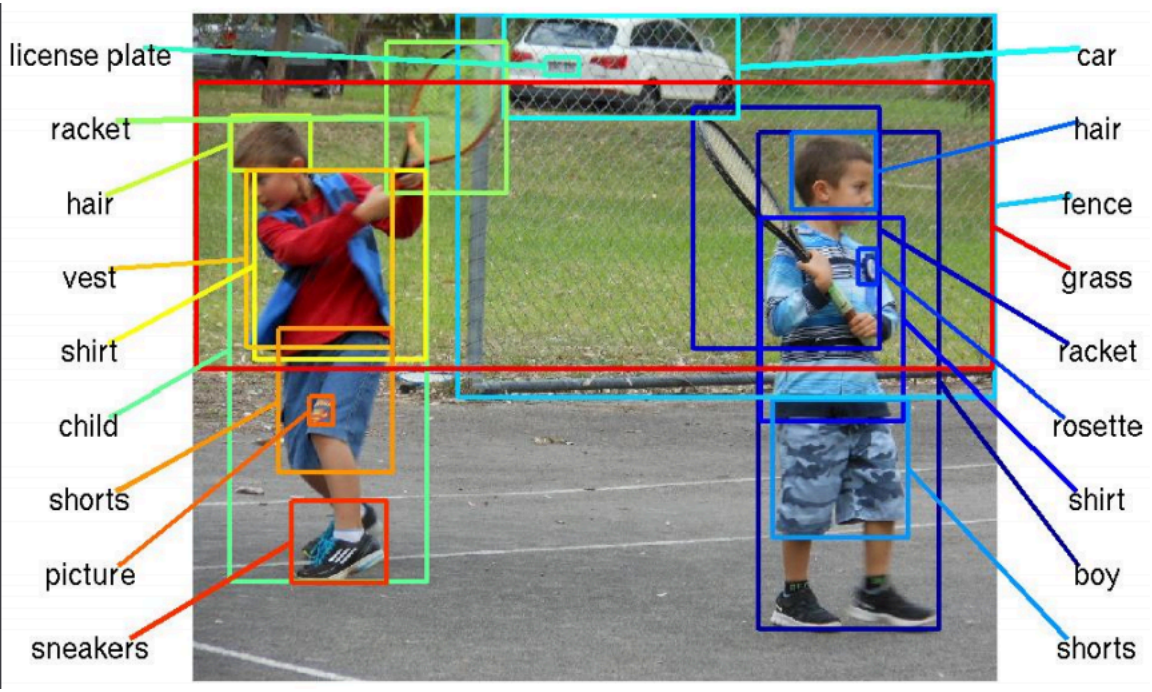
"construction worker in orange safety vest is working on road."

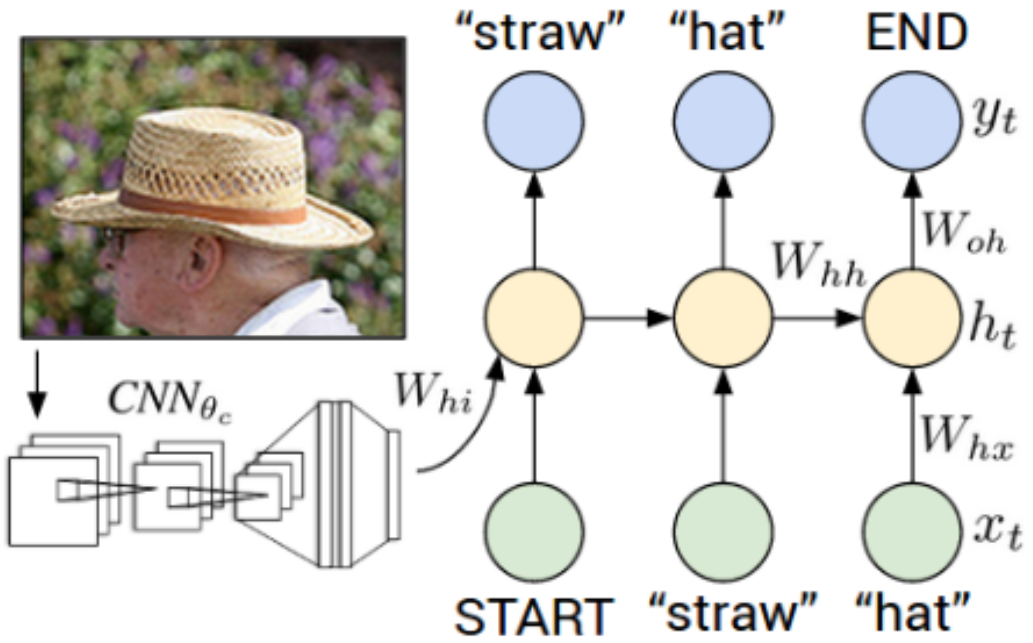
"two young girls are playing with lego toy."

Object Recognition & Caption

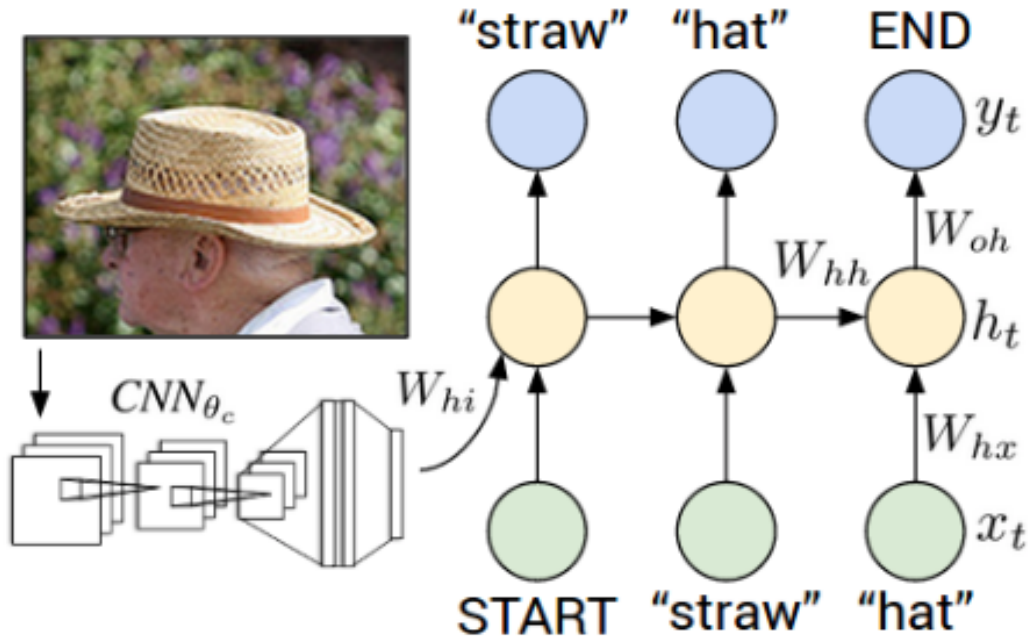


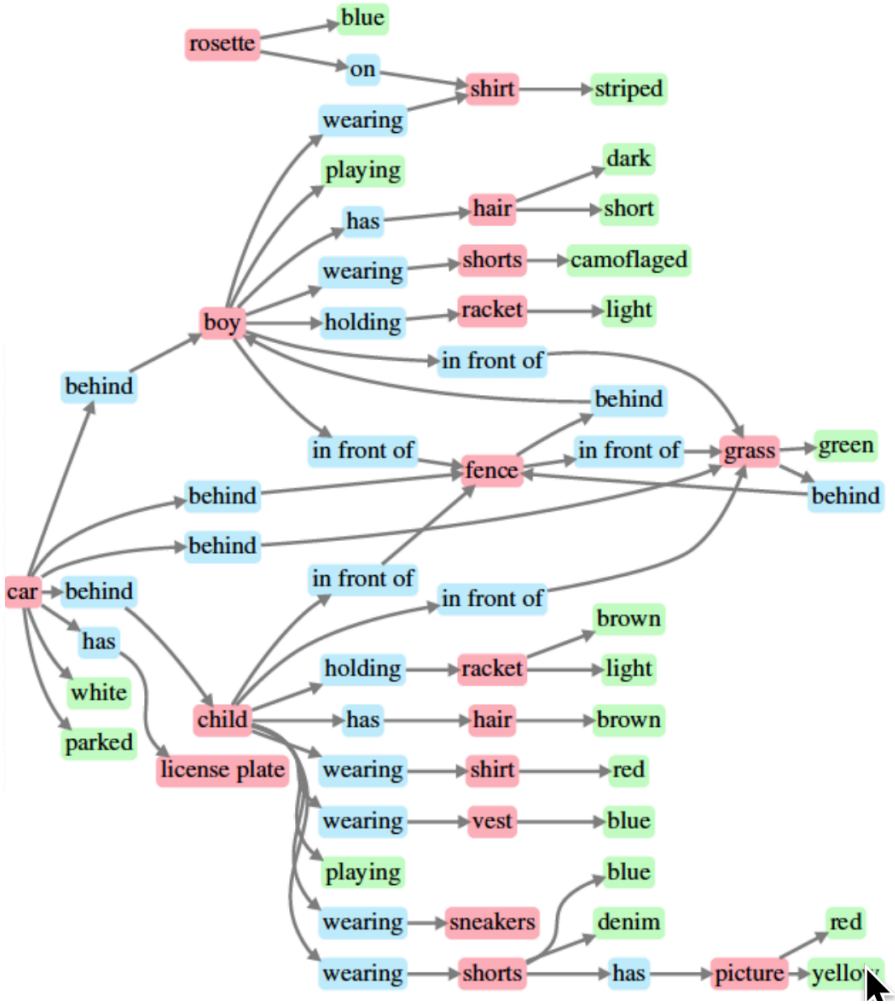
Object Recognition & Caption





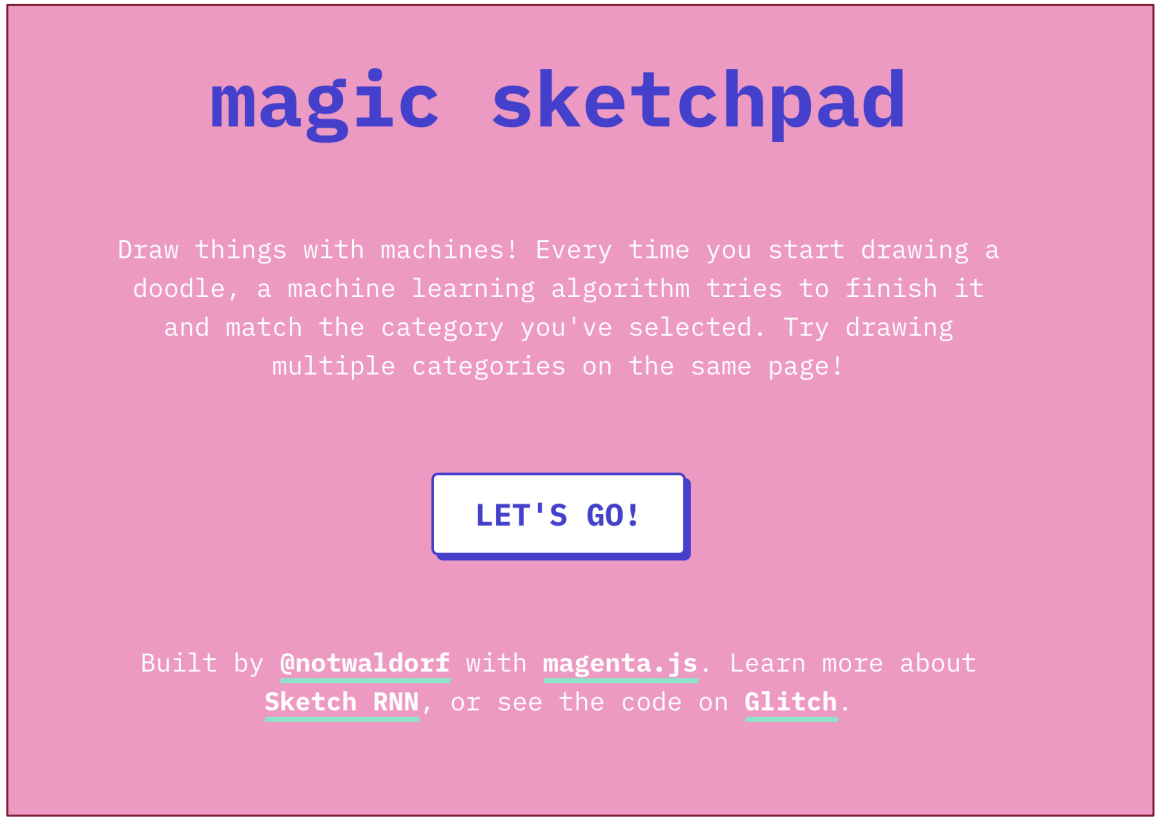
Object Recognition & Caption

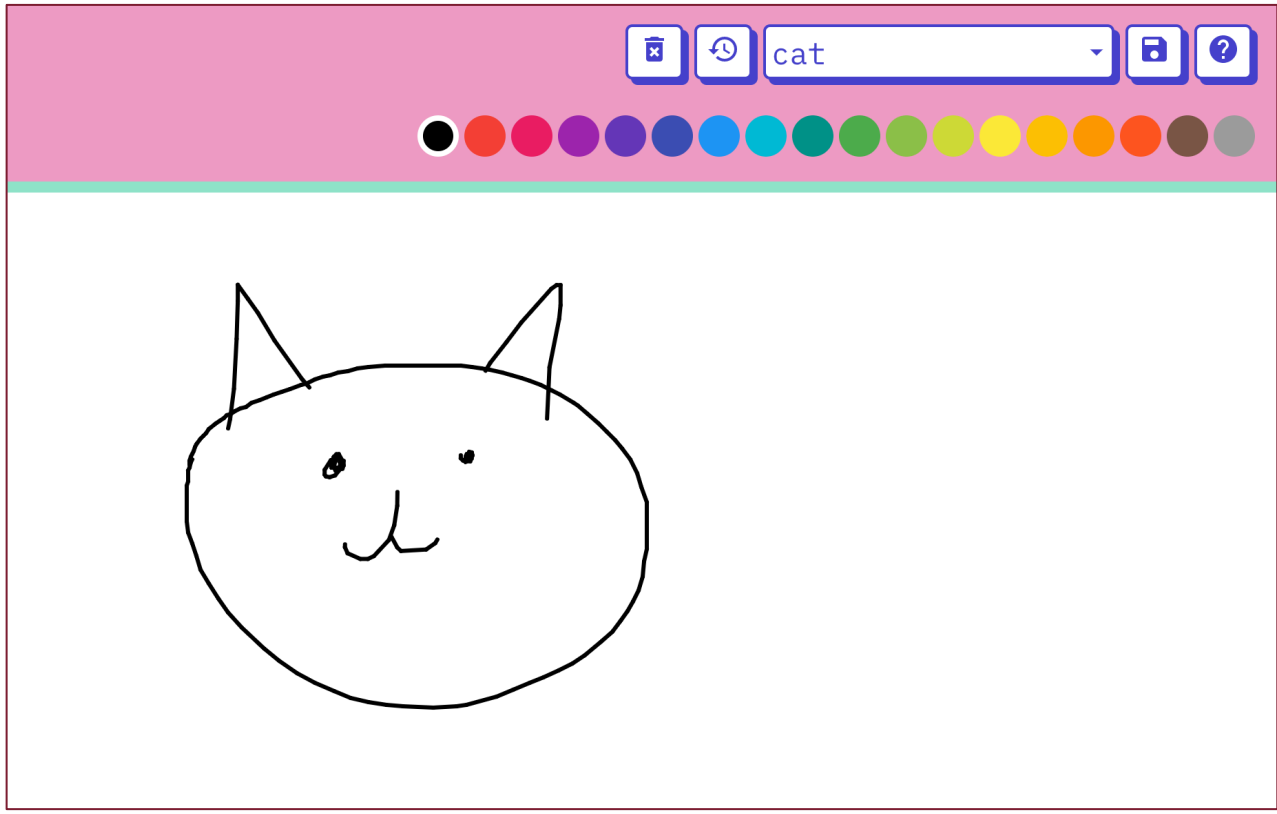


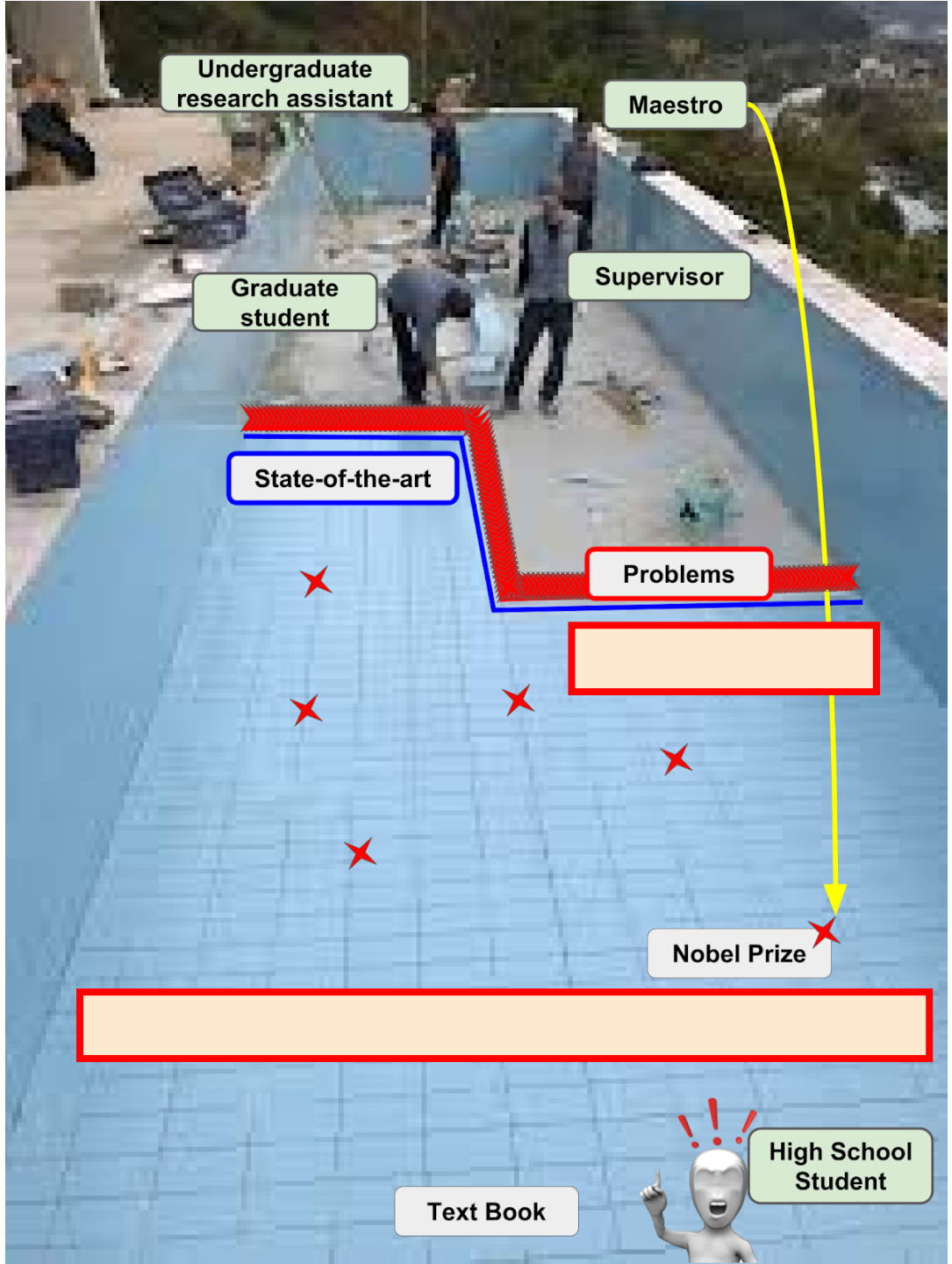


Sketch Net

https://magic-sketchpad.glitch.me/






Undergraduate research assistant
Maestro
Graduate student
Supervisor
State-of-the-art
Problems
Nobel Prize
Text Book
High School Student

머신러닝 어떻게 시작해야 하나요?

입사후 지난 5년 전

입사후 지난 5년 전

프로젝트 투입: 2016.04 ~ 2016.10

Big Data Project

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Just ETL based
on Open Technology

입사후 지난 5년: 다음 단계로

Big Data Project

==

ETL Project based

on Open Technology

Data Analysis

프로젝트 투입: 2016.04 ~ 2016.10

데이터 분석 관련 분야

커리큘럼: 데이터 사이언스 융학 학과

과정명	학점
데이터사이언스기초	3
기초통계	3
빅데이터처리	3
데이터분석언어	3
다변량통계	3
기계학습특론	3
인공지능	3
선형대수응용	3
웹마이닝	3
데이터모델링	3
데이터베이스시스템특론	3
빅데이터플랫폼특론	3
데이터시각화특론	3
자연어처리	3
최적화	3

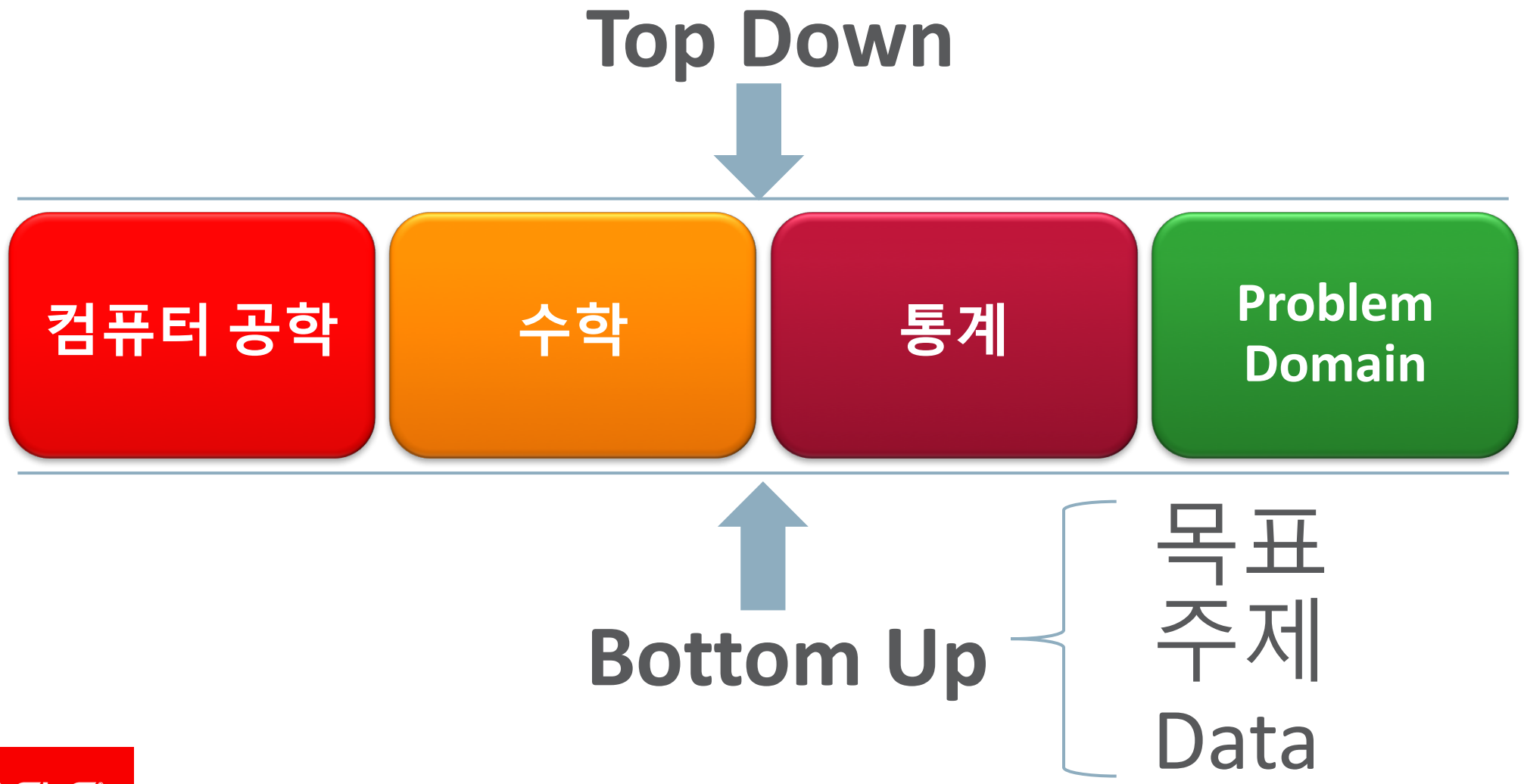
과정명	학점
응용데이터분석	3
딥러닝	3
서버시스템이해	3
정보보안특론	3
캡스톤프로젝트	3
비즈니스인텔리전스특론	3
빅데이터사례연구 I	3
빅데이터사례연구 II	3
논문연구	3
자료구조/알고리즘	3
IT와지적재산권보호	3
데이터사이언스응용	3
미디어콘텐츠분석기법	3
컴퓨터 비전	3

https://icon.skku.edu/icon/graduate/grad_data_curriculum.do?pager.offset=15

데이터 분석 관련 분야

입사후 지난 5년: 2017 ~ 현재 시행착오 연속

데이터 분석 관련 분야



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Applications & Platform Services


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