Use Case Tutorial

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2018/10/23

Agenda

- Overall Workflow
- Exploratory Data Analysis
- Feature Engineering + Training

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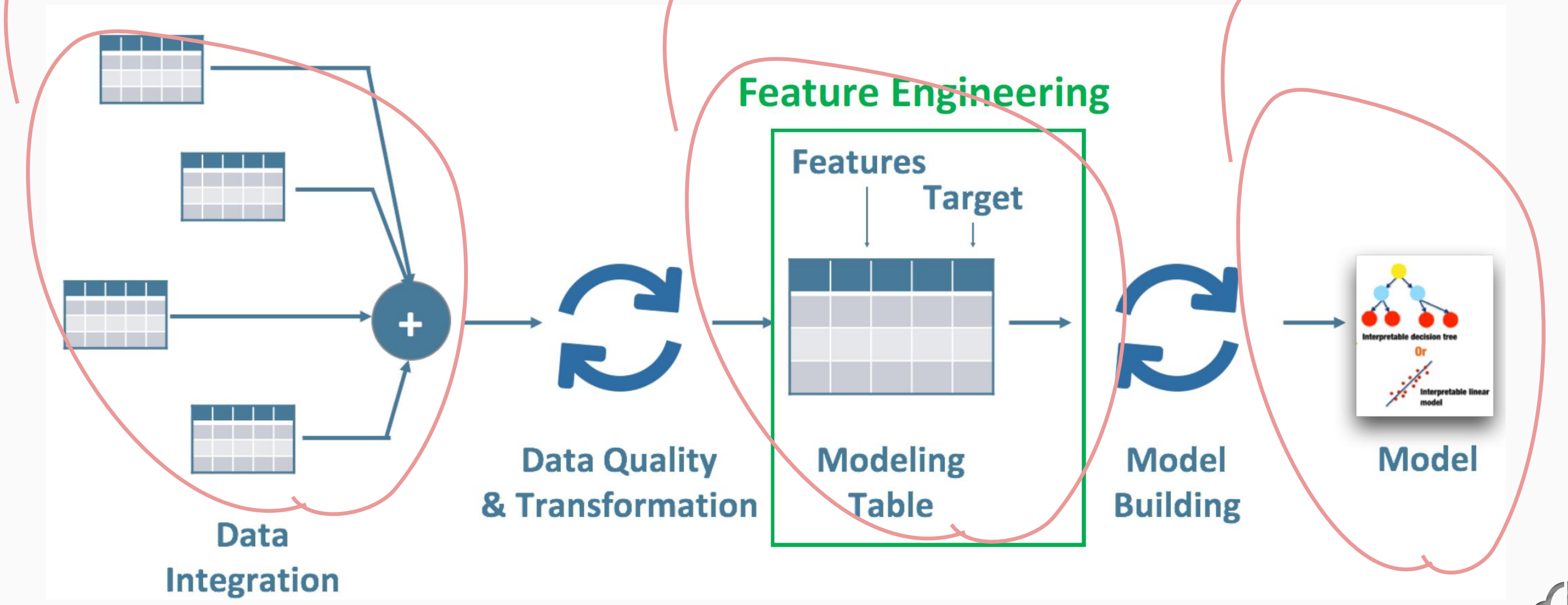
- Exploratory Data Analysis
- Feature Engineering + Training

Typical Enterprice Machine Learning Workflow

CSV(GCS), Cloud SQL, Big Query

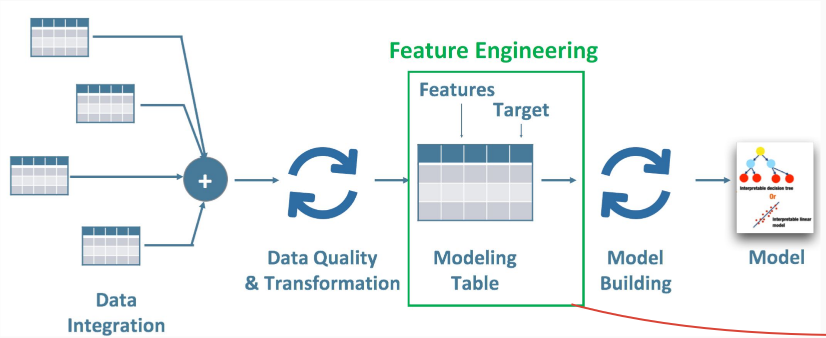
Python Script, Data Flow...

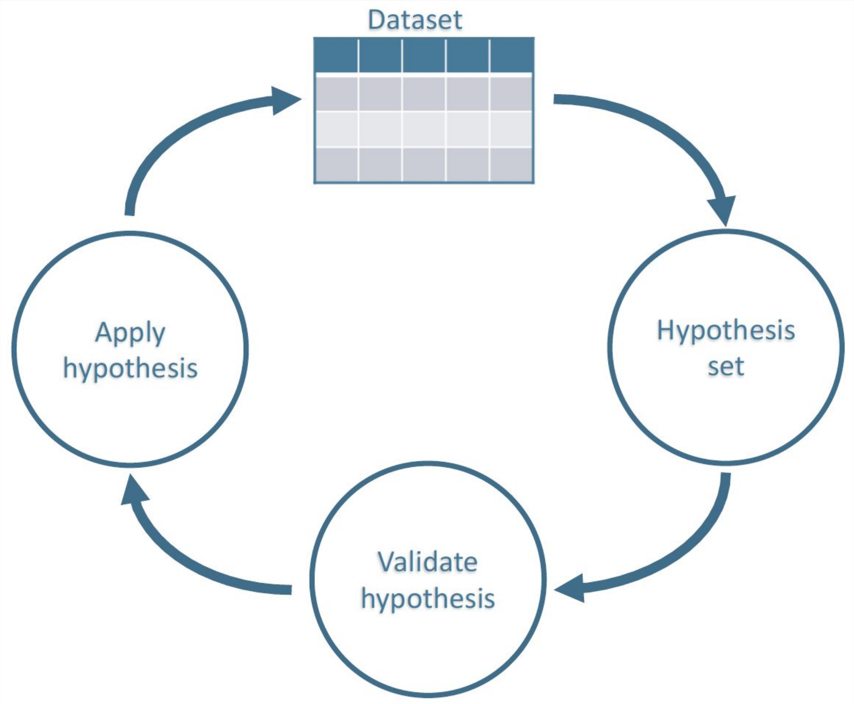
Deploy to ML-Engine,
Put Back to GCS...



Typical Enterprice Machine Learning Workflow

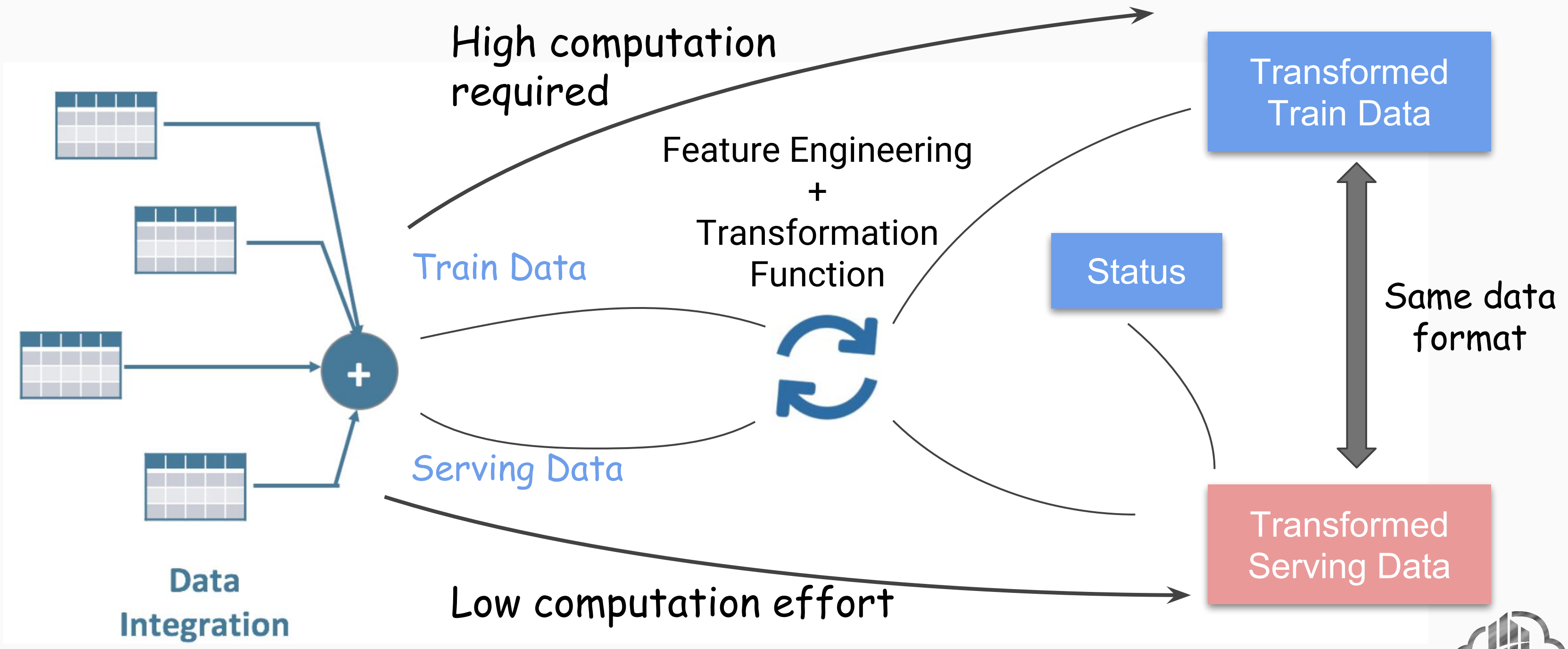
Feature Engineering cycle





Typical Enterprice Machine Learning Workflow

The Training and Serving



Agenda

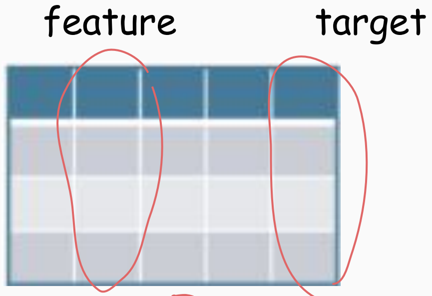
- Overall Workflow
- Exploratory Data Analysis
- Feature Engineering + Training

Type of Variable

- ❏ Numerical variable: “Float, Integer”
  - ❏ Discrete numerical variable
    e.g: `[1, 2, 3, 4]`
  - ❏ Continuous numerical variable
    e.g: `[1.23, 0.87, 1.5498, -0.3146]`
- ❏ Nominal (Categorical) variable: “String, Integer”
  e.g: Geography: `['France', 'Germany', 'Spain']`
  e.g: Address:
  `1F., No.1, Bilong Ln., Zhongzheng 1st Rd., Yingge Dist., New Taipei City 239, Taiwan (R.O.C.)`
  - ❏ Ordinal nominal variable: “String, Integer”
    e.g: Size of clothes: `['S', 'M', 'L', 'XL']`

What We Want to Explore

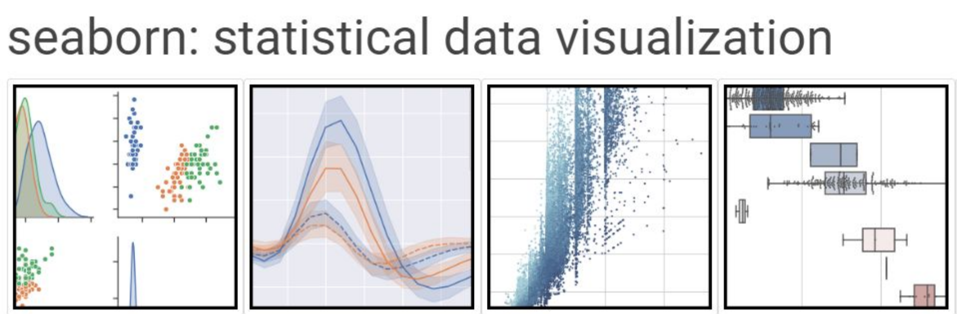
- ❑ Numerical variables:
  mean, std, median, quartiles, deciles
  data distribution (histogram)
- ❑ Nominal variables: frequency distribution
- ❑ Relationship between variables
  - ❑ Numerical x Numerical
  - ❑ Numerical x Nominal
  - ❑ Nominal x Nominal



What we care is the relation between **Feature and Label**

EDA Tools

Data read write, data clean, data transformation, data join ...



Data visualization

SM StatsModels Statistics in Python

Statistical test, basic model

Numerical Variable Visualized

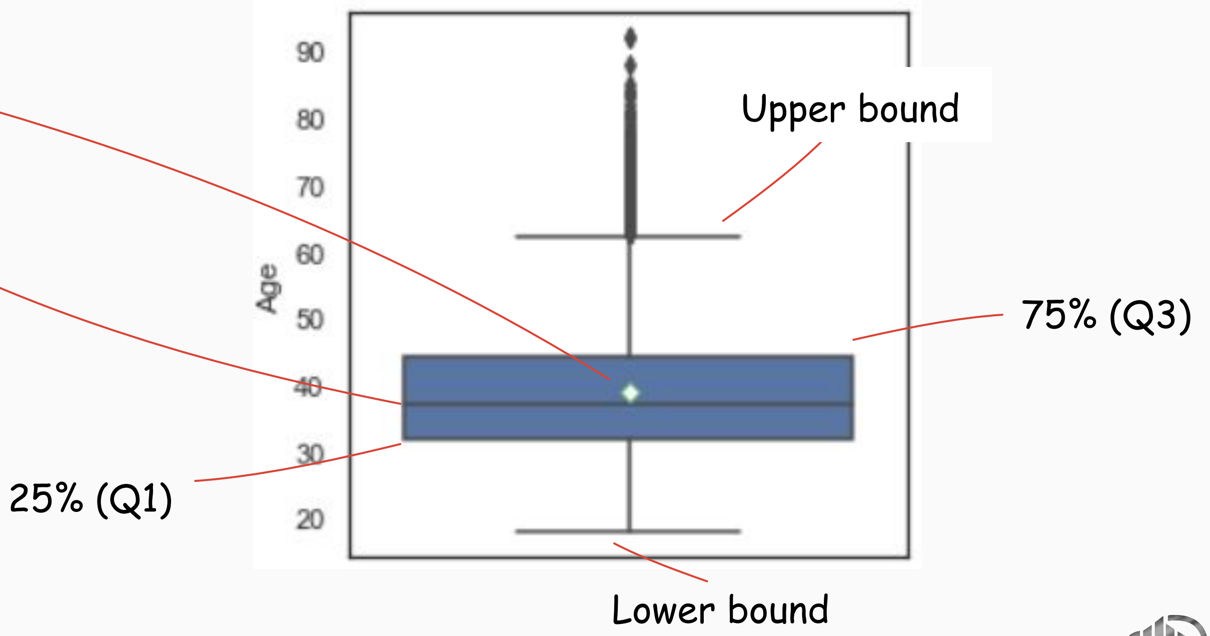
Visualization - Numerical Variable (Boxplot)

pandas.Series.describe()

```
raw.Age.describe()

count    7500.000000
mean       39.004267
std        10.500007
min        18.000000
25%        32.000000
50%        37.000000
75%        44.000000
max        92.000000
Name: Age, dtype: float64
```

```
sns.boxplot(raw.Age,
        showmeans=True, orient='v',
        meanprops={'marker':'D','markerfacecolor':'white'})
```



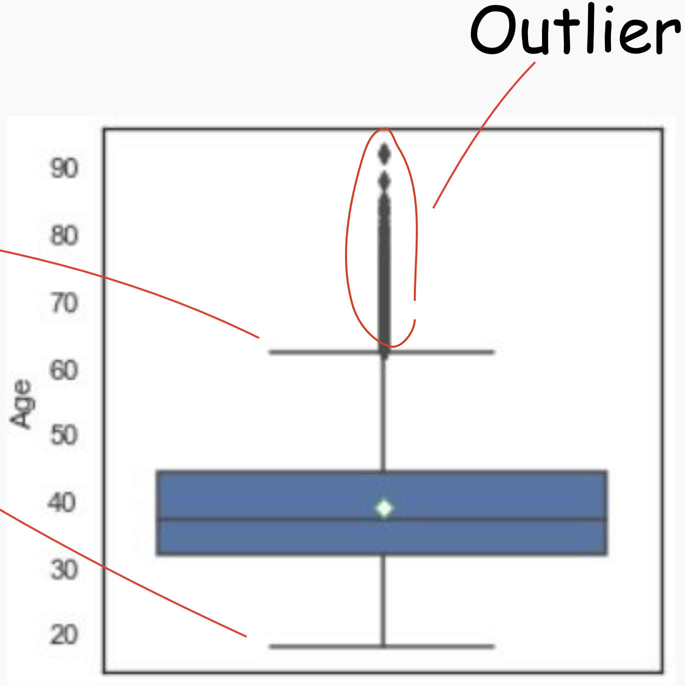
Visualization - Numerical Variable (Boxplot)

Interquatile range

IQR = Q3 - Q1

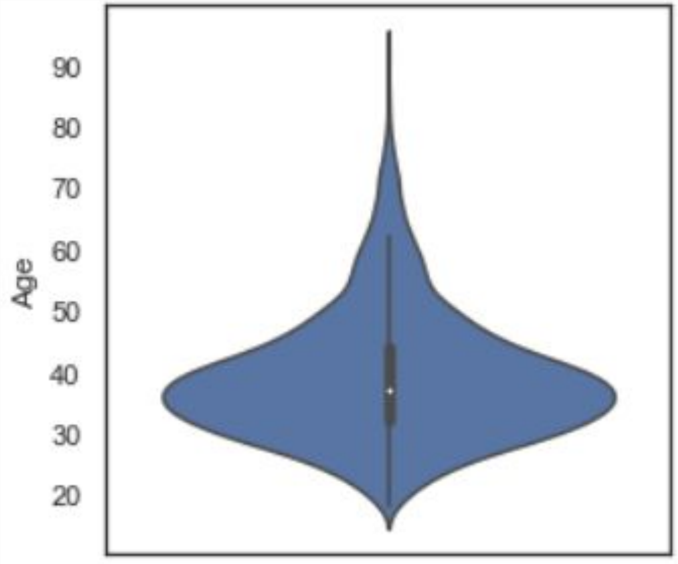
Upper bound = Q3 + IQR x 1.5

Lower bound = Q1 - IQR x 1.5



Visualization - Numerical Variable (Violinplot)

```
sns.violinplot(raw.Age, orient='v')
```

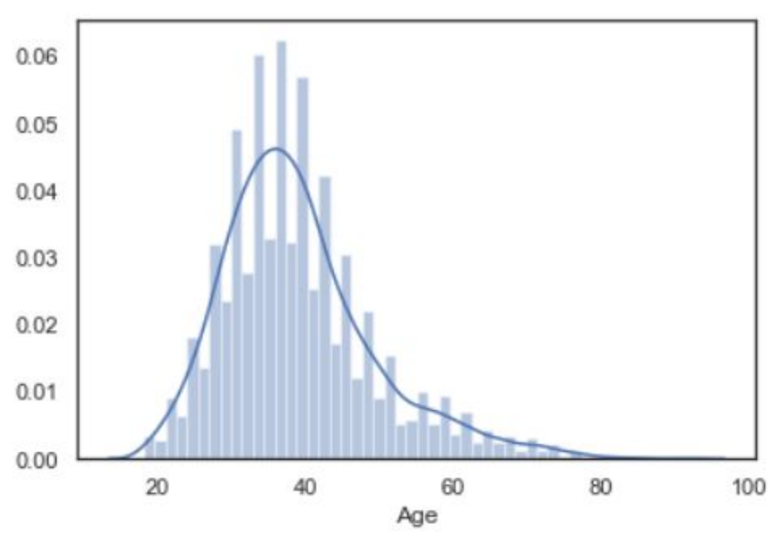


Include information

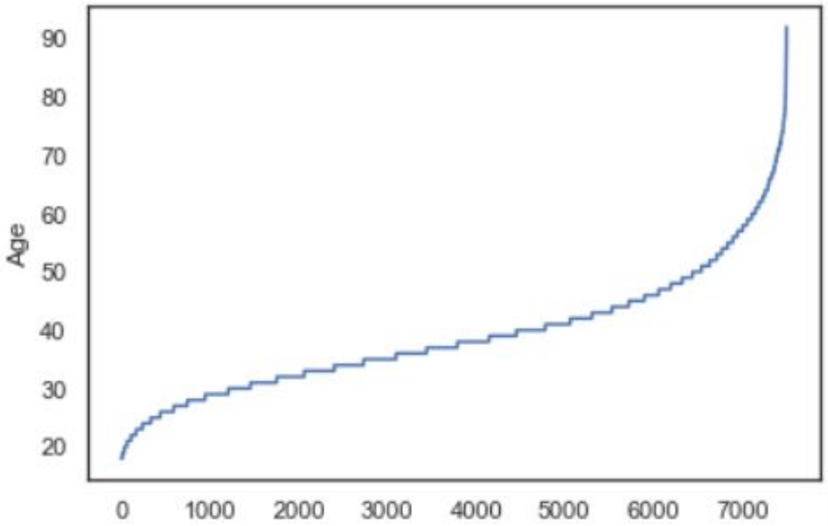
- Boxplot
- Data distribution

Visualization - Numerical Variable (Distplot, Lineplot)

```
sns.distplot(raw.Age)
```




```
sns.lineplot(
    np.arange(len(raw)),
    raw.Age.sort_values())
```



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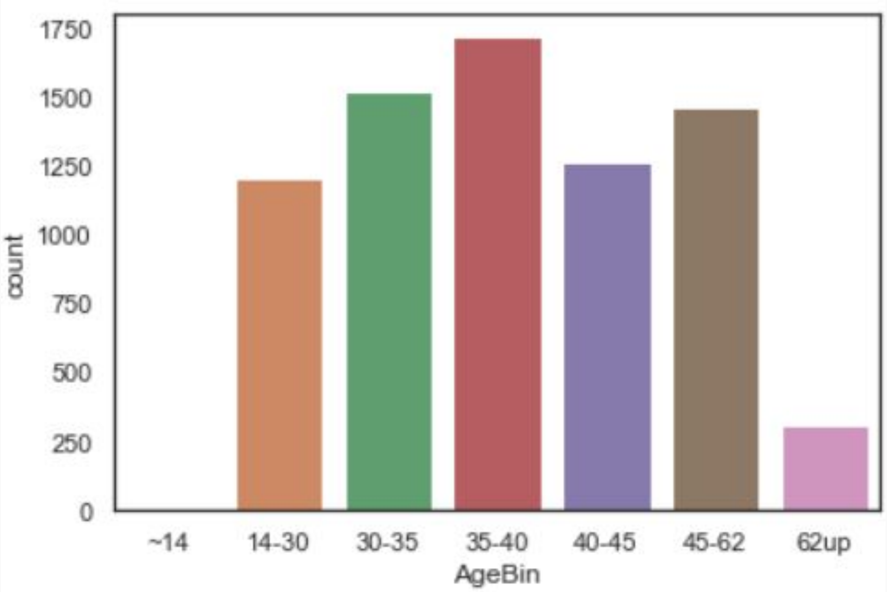
Nominal Variable Visualized

Visualization - Nominal Variable (Countplot)

```
sns.countplot(
    x="AgeBin",
    data=raw)
```



`pandas.Series.value_counts`

```
raw.AgeBin.value_counts()

14-30    1209.0
30-35    1525.0
35-40    1721.0
40-45    1267.0
45-62    1465.0
62up      313.0
Name: AgeBin, dtype:
float64
```

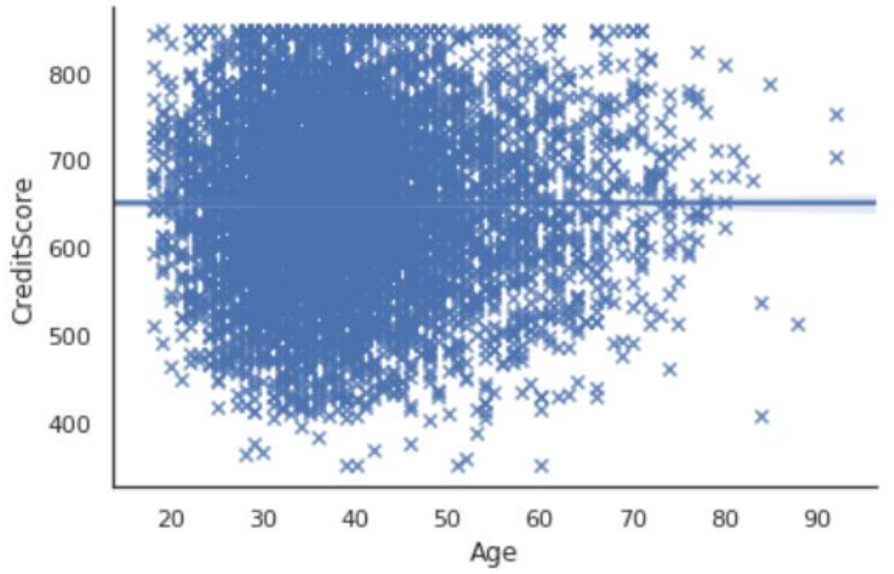
Multivariate Visualized

Multivariate Visualized - Numerical x Numerical

Regression Plot

⇒ sns.lmplot

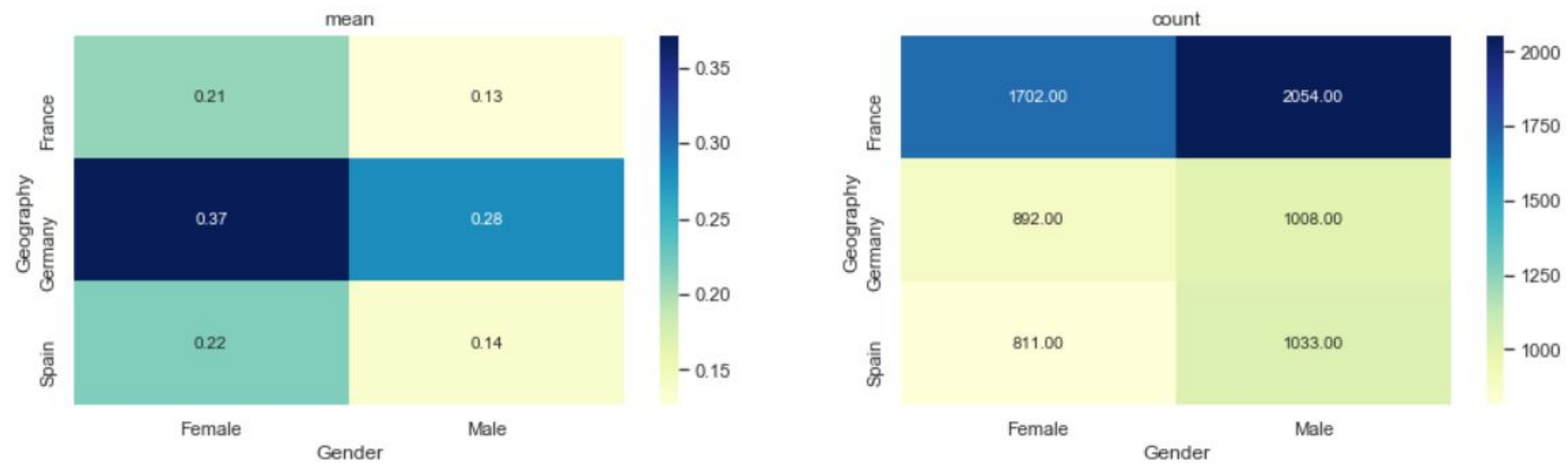
```
g = sns.lmplot(x='Age', y='CreditScore',
               # hue='Exited',
               data=raw, height=4, aspect=1.5, markers='x')
```



Multivariate Visualized - Nominal x Nominal

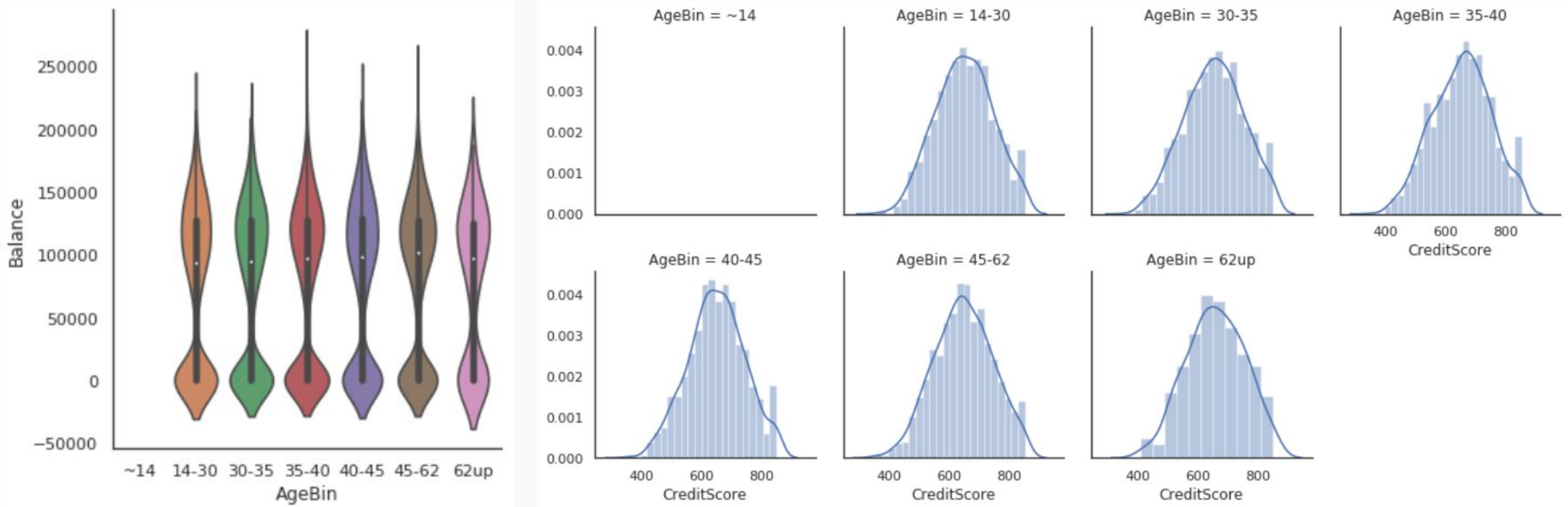
Heatmap ⇒ sns.heatmap

```
heatmap(raw, 'Geography', 'Gender', target='Claim')
```



Multivariate Visualized - Nominal x Numerical

Divide numerical variable by nominal variable !
⇒ Violinplot, Boxplot, Distplot, Lineplot ...



About The Statistical

Numerical x Numerical (Linear)

Pearson Correlation Coefficient

$$\rho = \frac{cov(X,Y)}{\sigma_x \sigma_y} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 (y_i - \bar{y})^2}}$$

$-1 < \rho < 1$

```
pd.DataFrame.corr()

data = data[
       ['Tenure', 'Balance', 'EstimatedSalary']]
data.corr(method='pearson')
```

	Tenure	Balance	EstimatedSalary
Tenure	1.000000	-0.012194	0.014443
Balance	-0.012194	1.000000	0.010461
EstimatedSalary	0.014443	0.010461	1.000000

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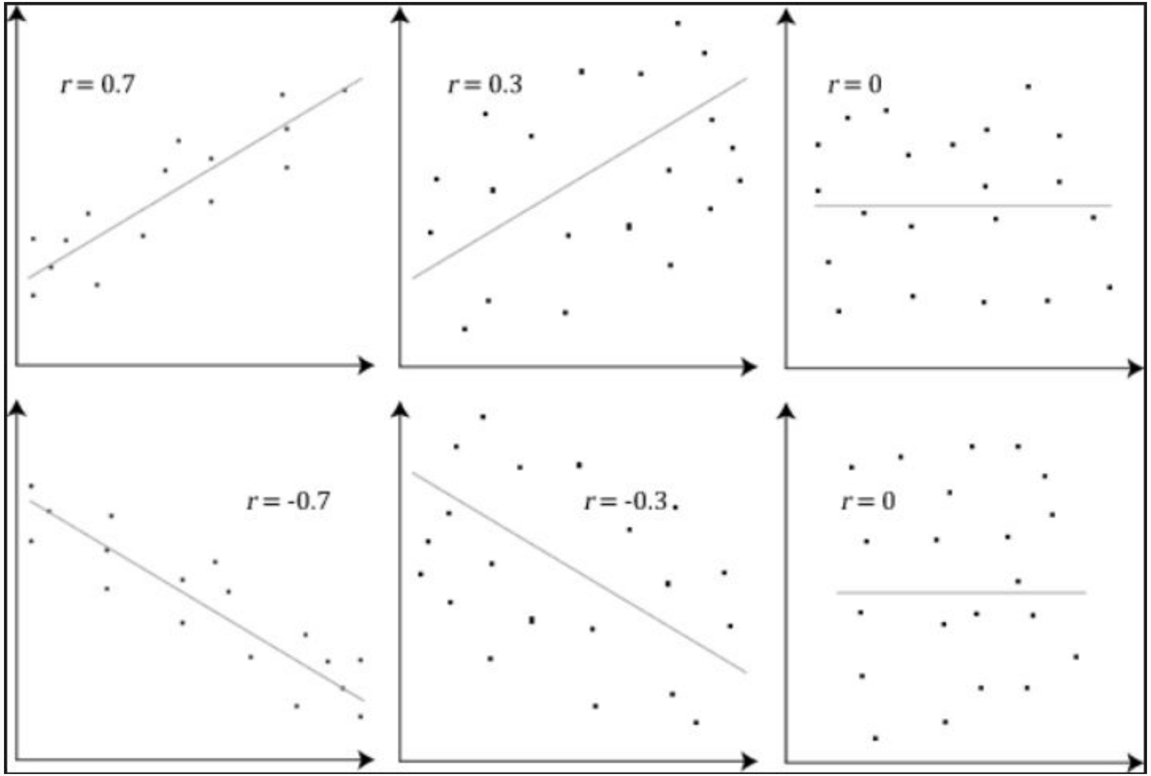
Numerical x Numerical (Linear)

Pearson Correlation Coefficient



Numerical x Numerical (Linear)

Spearman's rank correlation coefficient

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

Difference between rank of two variables

$-1 < \rho < 1$

Data size

```
pd.DataFrame.corr()

data = data[
      ['Tenure', 'Balance', 'EstimatedSalary']]
data.corr(method='spearman')
```

	Tenure	Balance	EstimatedSalary
Tenure	1.000000	-0.008285	0.014451
Balance	-0.008285	1.000000	0.006840
EstimatedSalary	0.014451	0.006840	1.000000

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Numerical x Numerical (Linear)

Spearman's rank correlation coefficient

	x	y	x_level	y_level	d_i	d_i^2
0	86	0	1	1	0	0
1	97	20	2	6	-4	16
2	99	28	3	8	-5	25
3	100	27	4	7	-3	9
4	101	50	5	10	-5	25
5	103	29	6	9	-3	9
6	106	7	7	3	4	16
7	110	17	8	5	3	9
8	112	6	9	2	7	49
9	113	12	10	4	6	36

$$\rho = 1 - \frac{6 \times 194}{10(10^2 - 1)} = -0.175175$$

Negative correlation,
but not significant

Beware the **scaler information lost**,
good for ordinal variable

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Chi-Square Test

About The Statistical Test

Before The Chi-Square Test ..., About The Statistical Experiment

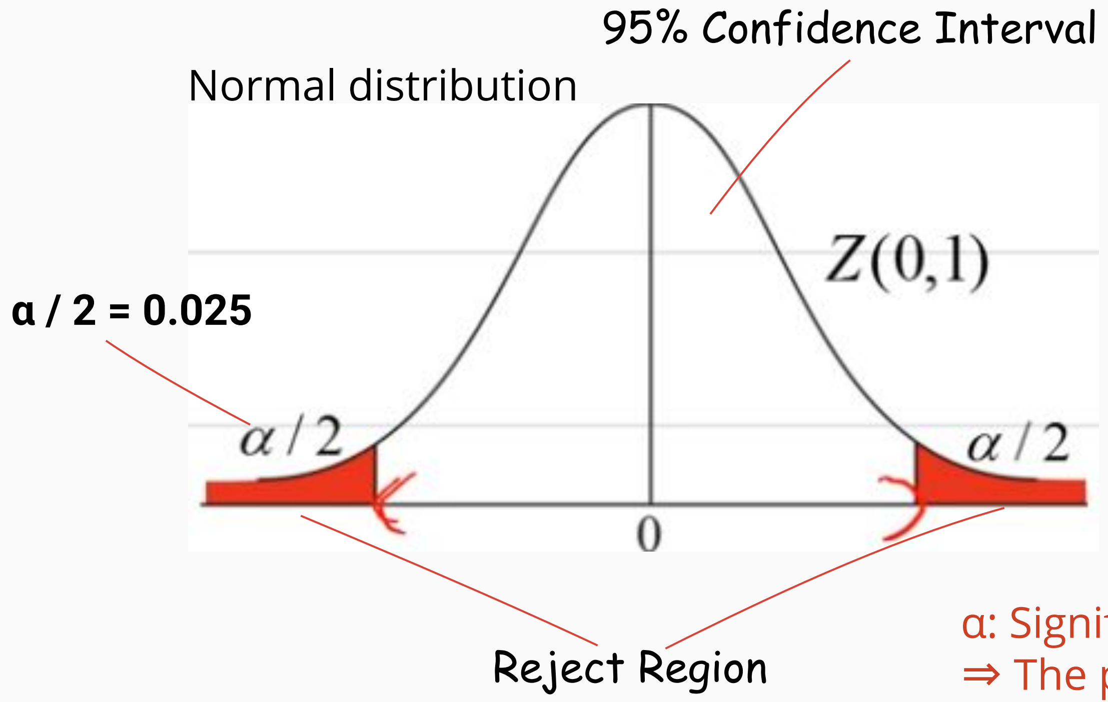
1. Hypothesis
   a. H_0: Null Hypothesis
      e.g: Vaiable **X_1, X_2** independent
   b. H_1: Alternative Hypothesis
      e.g: Vaiable **X_1** association with **X_2**

2. Significant Level **α**, Confidence Interval (1 - **α**)
   e.g: Given **α = 0.05,** means confidence interval = **0.95**

3. The p-value

4. When to reject H_0? (Means the result is significant)
   H_0: Negative event
   H_1: Positive event

About The Statistical Test



		Prediction H_0	Prediction H_1
Ground Truth	H_0	TN	FP
Ground Truth	H_1	FN	TP

Type I error => FP

Type II error => FN

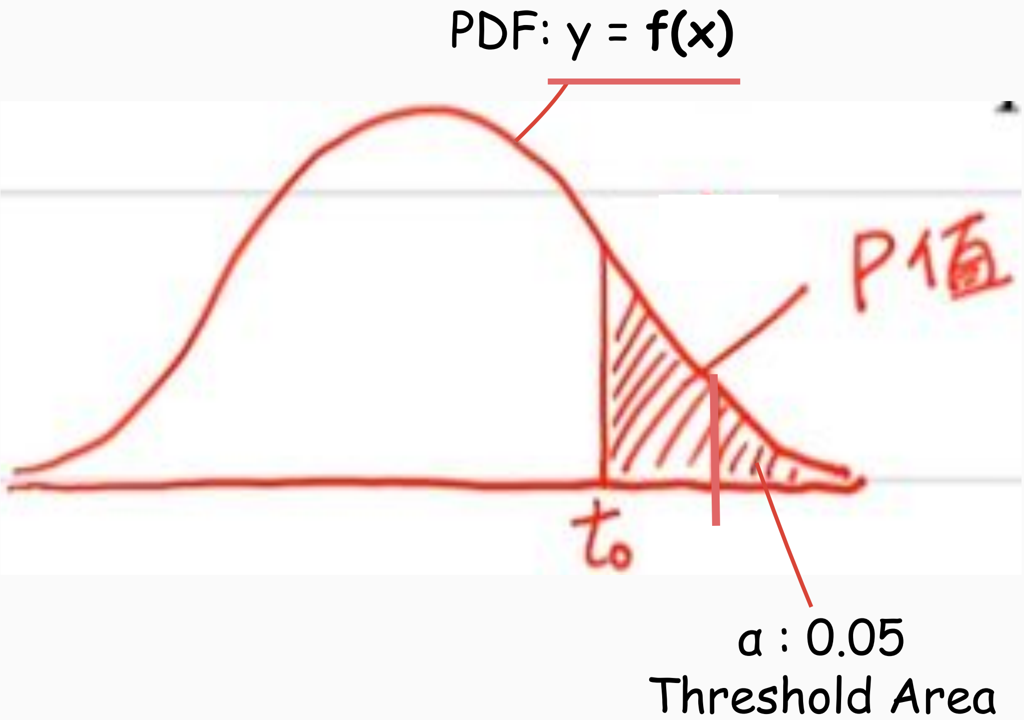
α: Significant level

⇒ The probability of type I error occured

[Example of Type I II error]

About The Statistical Test

When is the experiment significant?



PDF: Probability Density Function

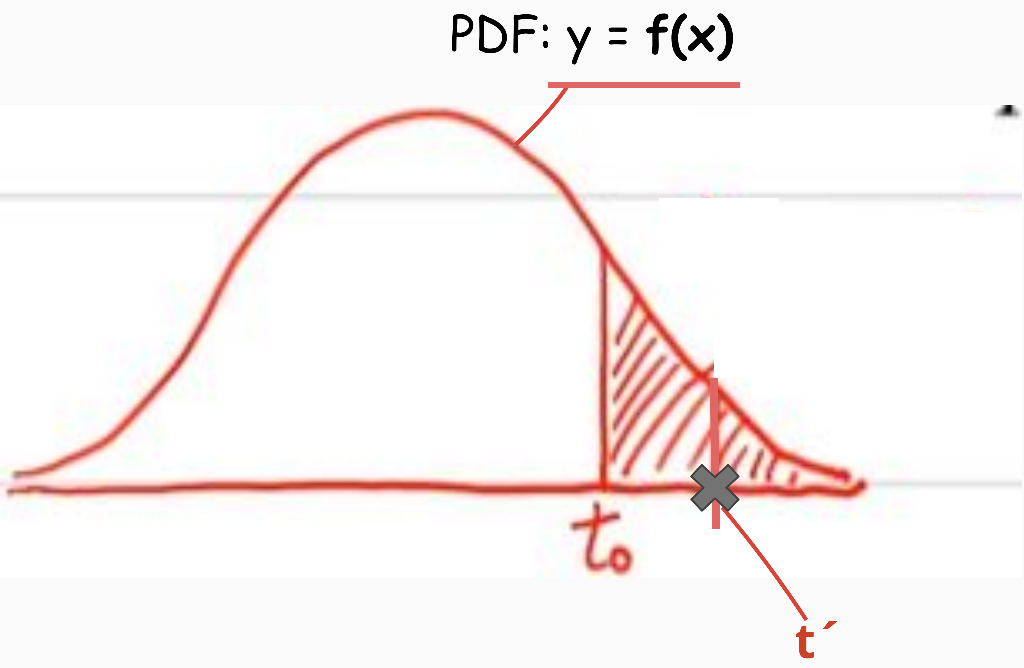
t_0: Statistic value

p-value: Area under **PDF** and **t_0**

$P < \alpha$: Reject H_0
$P >= \alpha$: Not reject H_0

About The Statistical Test

When is the experiment significant?



PDF: Probability Density Function

t_0: Statistic value

$t_0 > t'$: Reject H_0
$t_0 <= t'$: Not reject H_0

About The Statistical Test

- Goodness of Fit
  - H_0: There is no difference between the observed and expected frequencies
  - H_1: There is a difference between the observed and the expected frequencies

- Test for homogeneity
  - H_0: Populations follow the same probability distribution
  - H_1: One of populations dosen't follow the specific probability distribution

- Test for Independent
  - H_0: Nominal vaiables $\mathbf{X_1}$, $\mathbf{X_2}$ independent
  - H_1: Nominal vaiables $\mathbf{X_1}$ association with $\mathbf{X_2}$

About The Statistical Test

H_0: Vaiable $\mathbf{X_1}$, $\mathbf{X_2}$ independent H_1: Vaiable $\mathbf{X_1}$ association with $\mathbf{X_2}$

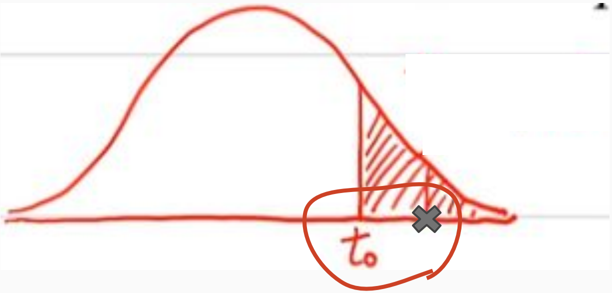
marit	educ
Never married	PhD or higher
Married	Middle school or lower
Divorced	Bachelor's
Widowed	PhD or higher
Married	PhD or higher

Marital Status by Education | n = 300

	Middle school or lower	High school	Bachelor's	Master's	PhD or higher	Total
Never married	18	36	21	9	6	90
Married	12	36	45	36	21	150
Divorced	6	9	9	3	3	30
Widowed	3	9	9	6	3	30
Total	39	90	84	54	33	300

$$\chi^2 = \sum_i \frac{(Actual_i - Expected_i)^2}{Expected_i}$$

t_0: Chi-Square Statistic Value



Nominal x Nominal (Non-Linear): Chi-Square Test

H_0: Vaiable $\mathbf{X_1}$, $\mathbf{X_2}$ independent H_1: Vaiable $\mathbf{X_1}$ association with $\mathbf{X_2}$

Marital Status by Education | n = 300

	Middle school or lower	High school	Bachelor's	Master's	PhD or higher	Total
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Total	39	90	84	54	33	300

$$\chi^2 = \sum_i \frac{(Actual_i - Expected_i)^2}{Expected_i}$$

Assume the events between **Education** and **Marital** status are mutual independent

$$P(A \cap B) = P(A)P(B)$$

P(**Education** and **Marital**) = P(**Education**) x P(**Marital**)

Nominal x Nominal (Non-Linear): Chi-Square Test

H_0: Vaiable $\mathbf{X_1}$, $\mathbf{X_2}$ independent H_1: Vaiable $\mathbf{X_1}$ association with $\mathbf{X_2}$

Marital Status by Education | n = 300

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Widowed	3	9	9	6	3	30
Total	39	90	84	54	33	300

$$\chi^2 = \sum_i \frac{(Actual_i - Expected_i)^2}{Expected_i}$$

Actual(**Master's** x **Married**) = 36
Expected(Master's x Married) = P(**Master's**) x P(**Married**) x Length(data)
= (54 / 300) x (150 / 300) x 300
= 0.18 x 0.5 x 300
= 27

⇒ $(36 - 27)^2 / 27 = 3.0$

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Nominal x Nominal (Non-Linear): Chi-Square Test

statsmodels package example

```
# Calculate chi-square value, p-value, degree of freedom, expected value
chi, pv, df, expected = stats.chi2_contingency(observed=data)

# check if chi-square value > criterion(95% confidence interval)
crit = stats.chi2.ppf(q=0.95, df=df)

print(f'chi-square value: {chi}, criterion: {crit}')
```

```
chi-square value: 1022.025, criterion: 11.070
result: True
```

Significant! Reject H_0
There is a relationship between X_1, X_2

Nominal x Nominal (Non-Linear): Chi-Square Test

Utilize The Concept of The Chi-Sqaure Independent Test

Find new vocabulary for **Jieba**

- ➔ N-gram
  - ◆ 球不是這麼踢滴 ⇒ (2-gram) [球不, **不是**, 是這, **這麼**, 麼踢, 踢滴]

```python
s = "球不是這麼踢滴"
n_win = 2
[s[i:i + n_win]
 for i in range(len(s) - n_win + 1)]
```

```
['球不', '不是', '是這', '這麼', '麼踢', '踢滴']
```

- ➔ Long term first
  skip short term in the long term
  - ◆ 台灣大哥大 ⇒ Skip [台灣] [大哥]

Nominal x Nominal (Non-Linear): Chi-Square Test

Utilize The Concept of The Chi-Sqaure Independent Test

- 何者更適合成詞?
  - "的電影"-> 389次
  - "電影院"-> 175次

假設**電影**是已知詞

- 可以根據機率計算成詞可能性
  - 2400萬字的文本資料中，"電影"一共出現了2774次，出現的概率約為0.000113。"院"字則出現了4797次，出現的概率約為0.0001969
  - 如果兩者之間真的毫無關係，它們恰好在一起的概率就應該是0.000113×0.0001969，約為2.223 * 10^ –8
  - "電影院"在語料中一共出現了175次，出現概率約為7.183乘以10的–6次方，是預測值的300多倍

Expection = P(電影)P(院)

Actual

Nominal x Nominal (Non-Linear): Chi-Square Test

Utilize The Concept of The Chi-Sqaure Independent Test

- "的"字的出現概率約為0.0166，因而"的"和"電影"隨機組合到了一起的理論概率值為0.0166×0.000113，約為1.875*10^–6，真實概率約為1.6乘以10的–5次方，是預測值的8.5倍

P(電影院) / P(電影)P(院) ==> 300 Winner

P(的電影) / P(的)P(電影) ==> 8.5

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ANOVA (Analysis of Variance)

Nominal x Numerical (Non-Linear): ANOVA

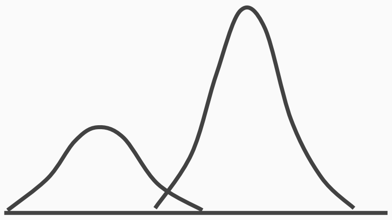
Assume we have k group, k > 1

H_0: $\mu 1 = \mu 2 \ \ldots = \mu k$

H_1: Means are not all equal.

Prerequisite

- ➔ Each groups approximately follow **normal distribution (Guassian distribution)**
- ➔ Independent cases
- ➔ Equality (or "homogeneity") of variances



Welch test, Brown Forsythe test...

??% Confidence in ANOVA test

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Nominal x Numerical (Non-Linear): ANOVA

Assume we have k group, k > 1

H_0: $\mu 1 = \mu 2 \ \ldots = \mu k$

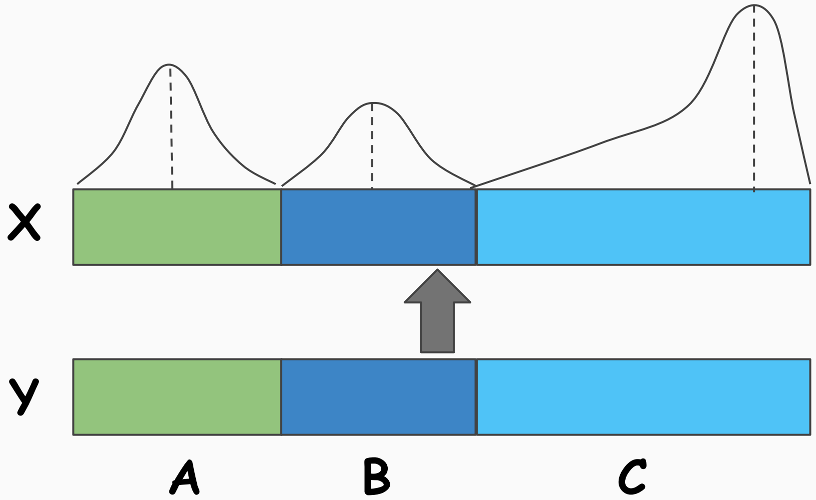
H_1: Means are not all equal.

Prerequisite

- ➔ Each groups approximately follow **normal distribution (Guassian distribution)**
- ➔ Independent cases
- ➔ Equality (or "homogeneity") of variances

X: Numerical variable

Y: Nominal variable



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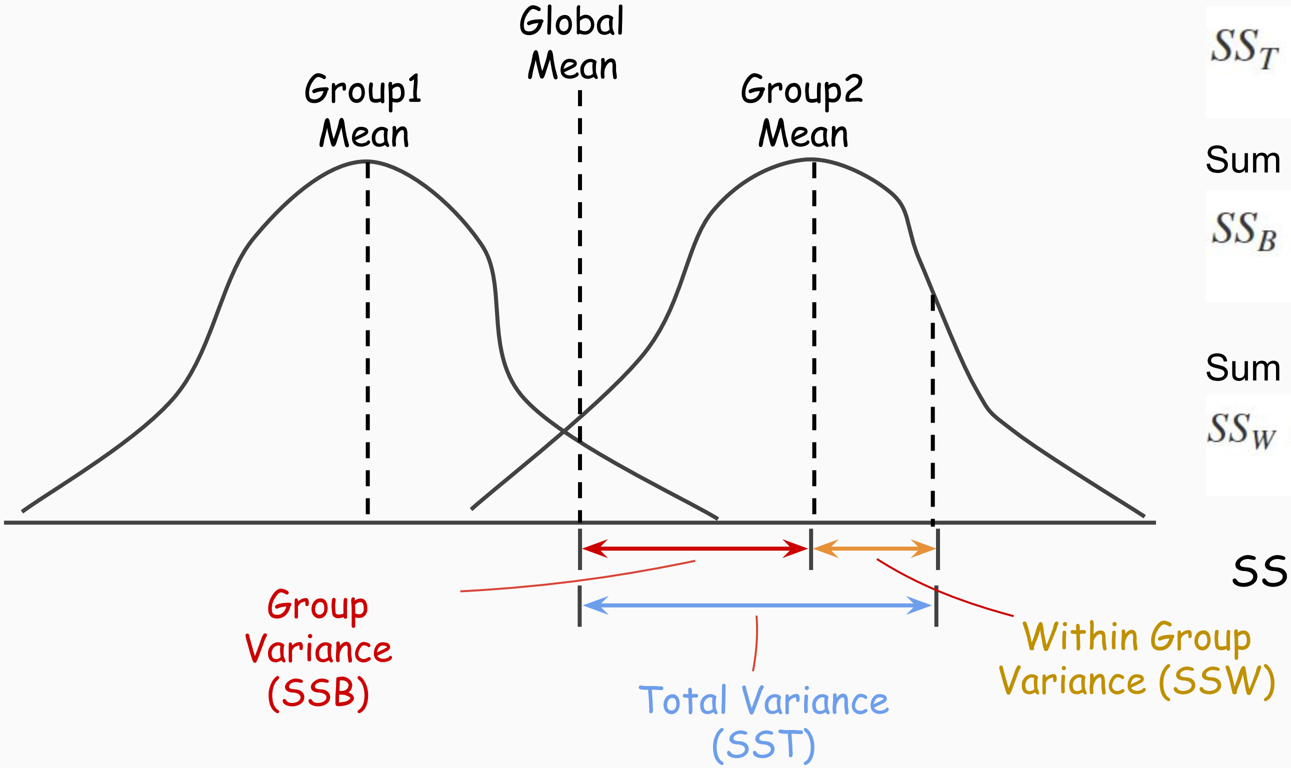
Nominal x Numerical (Non-Linear): ANOVA



Total sum of square

$$SS_T = \sum_i (X_i - \overline{X_{all}})^2$$

Sum of square between groups

$$SS_B = \sum_{\#group} (\overline{X_{group}} - \overline{X_{all}})^2$$

Sum of square within groups

$$SS_W = \sum_{\#group} \sum_{\#within\_group} (X_i - \overline{X_{group}})^2$$

SST = SSB + SSW

Nominal x Numerical (Non-Linear): ANOVA

$$MS_B = \frac{SS_B}{df_B}$$

$$MS_W = \frac{SS_W}{df_W}$$

$$\Rightarrow \frac{MS_B}{MS_W}$$

	SS	DF	MS	F	P
B	SS_B	G - 1	MS_B	MS_B / MS_W	P-value
W	SS_W	(N - 1) - (G - 1)	MS_W		
T	SS_T	(N - 1)			

We hope the F Larger

Area => P < α: Reject H_0
P >= α: Not reject H_0

Total sum of square

$$SS_T = \sum_i (X_i - \overline{X_{all}})^2$$

Sum of square between groups

$$SS_B = \sum_{\#group} (\overline{X_{group}} - \overline{X_{all}})^2$$

Sum of square within groups

$$SS_W = \sum_{\#group} \sum_{\#within\_group} (X_i - \overline{X_{group}})^2$$

Nominal x Numerical (Non-Linear): ANOVA

statsmodels package example

```
def anova(formula, data):
    table  = sm.stats.anova_lm(
        ols(formula, data=data).fit(),
        typ=2
    )
    return table

anova("Age ~ C(Claim)", data=data)
```

"Numerical ~ C(Nominal)"

	sum_sq	df	F	PR(>F)
C(Claim)	63991.391600	1.0	629.02925	2.266897e-133
Residual	762774.471867	7498.0	NaN	NaN

P-value

Recap

- Single Variable
  - Numerical variable ⇒ Boxplot, Violinplot, Distplot, Lineplot
  - Nominal variable ⇒ Countplot

- Multi-Variable
  - Numerical x Numerical ⇒ Regression plot
  - Nominal x Nominal ⇒ Heatmap
  - Nominal x Numerical ⇒ Conditional Boxplot, Conditional Violinplot ...

- Relationship
  - Numerical x Numerical ⇒ Pearson, Spearman Correlation Coefficient
  - Nominal x Nominal ⇒ Chi-Square
  - Nominal x Numerical ⇒ ANOVA

Lab: Exploratory Data Analysis

Topic : Exploratory Data Analysis

Filename	lab_eda_insurance_claim.ipynb
Data	Financial Customer Churn Prediction
Target	➔ Understand the data ➔ Features distribution ➔ Relationship between features or between features and label
Duration	About 20 min

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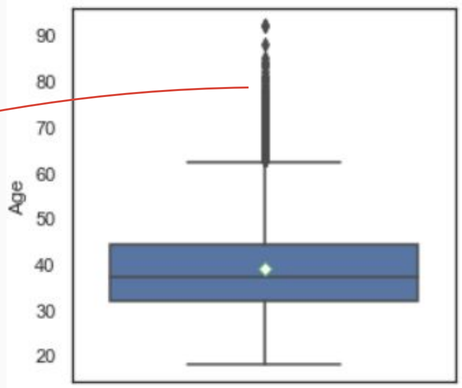
Agenda

- Overall Workflow
- Exploratory Data Analysis
- Feature Engineering + Training

Basic - Data Clean

- ➔ Missing value in numerical variable
  - ◆ Fill **mean** or **median**
- ➔ Outlier in numerical variable
  - ◆ Utilize the quartile to find **outlier,** and fill mean or median

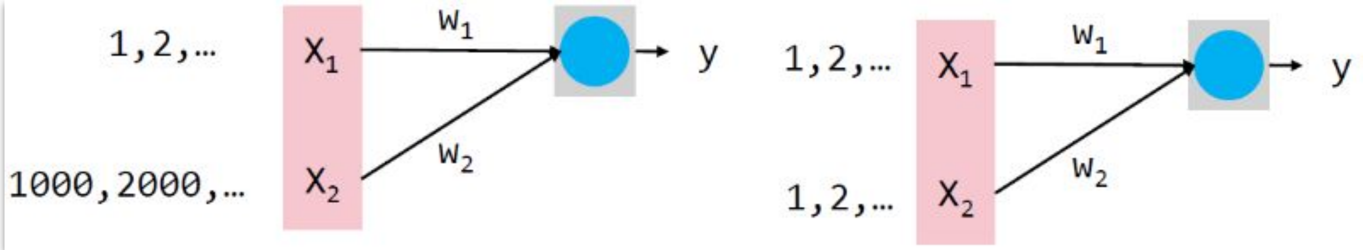


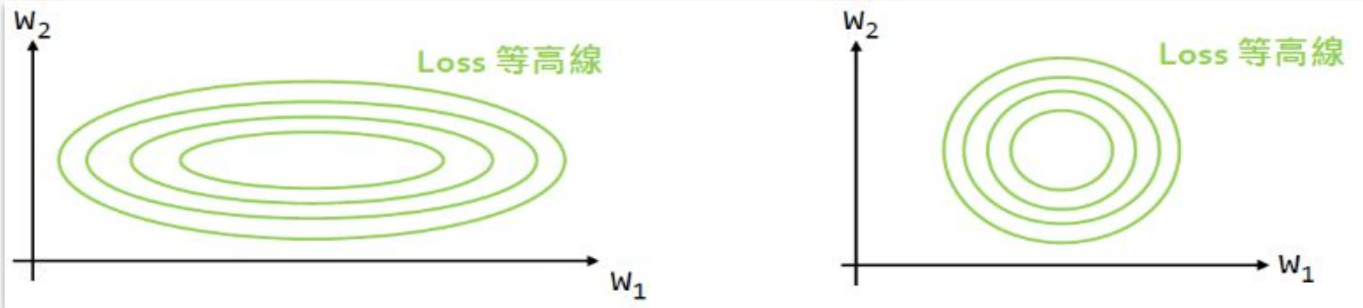
- ➔ Missing value in nominal variable
  - ◆ See missing value as an special class
  - ◆ Add a feature to describe missing value

nominal column	added
A	0
NaN	1
B	0

Basic

Numeric variable ⇒ Normalization





Basic

Numeric variable ⇒ Normalization

➔ Min max scaler to [0, 1] **(Beware outlier)**

$$\frac{x_i - min}{max - min}$$

➔ Scale to standard normal distribution (Z-score standardize)

$$\mu = 0, \ \sigma = 1$$

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Basic

Nominal variable ⇒ One Hot Encoding

column
class A
class B
class C

1
2
3

1	0	0
0	1	0
0	0	1

all the pairwise distance are the same ⇒ sqrt(2)

Before Advanced Feature Engineering

Before Advanced Feature Engineering

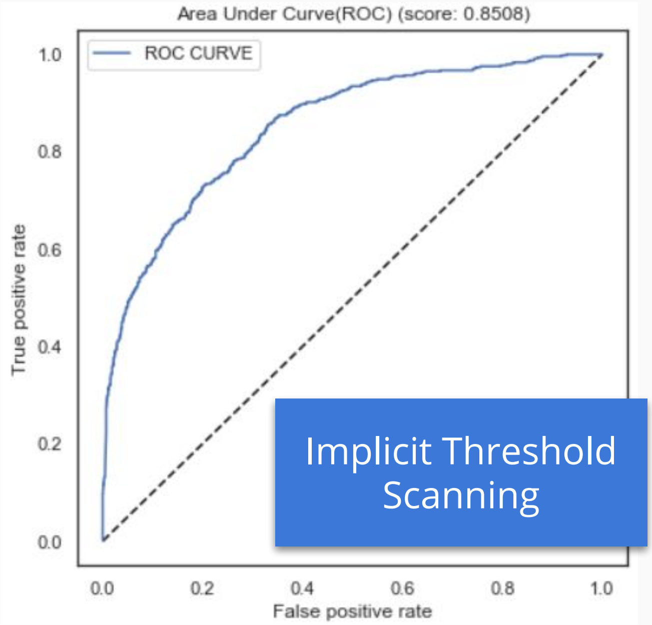
Topic : Knowing Programing Structure

Filename	lab_model_insurance_claim.ipynb
Data	Financial Customer Churn Prediction
Target	
Duration	

Before Advanced Feature Engineering

ROC: Receiver Operating Characteristic

TP Rate cross FP Rate
(0 < AUC < 1)



Implicit Threshold Scanning

AUC = 0.5 (no discrimination)
0.7 ≦ AUC ≦ 0.8 (acceptable discrimination)
0.8 ≦ AUC ≦ 0.9 (excellent discrimination)
0.9 ≦ AUC ≦ 1.0 (outstanding discrimination)

		Prediction 0	Prediction 1
Ground Truth	0	TN	FP
	1	FN	TP

FP Rate = FP / (TN + FP)

TP Rate = TP / (FN + TP)

Before Advanced Feature Engineering

AUROC (Code)

```
from sklearn.metrics import roc_curve, auc

fpr, tpr, thres = roc_curve(y, pred, pos_label=1)
auc_scr = auc(fpr, tpr)
```

	fpr	tpr	threshold
0	0.000000	0.002045	0.999386
1	0.000000	0.104294	0.883024
2	0.000497	0.104294	0.880933
3	0.000497	0.110429	0.870801
4	0.000995	0.110429	0.870346
5	0.000995	0.118609	0.852421

Before Advanced Feature Engineering

Find Best Threshold ⇒ F Beta Score

$$F_\beta = (1 + \beta^2) \cdot \frac{\text{precision} \cdot \text{recall}}{(\beta^2 \cdot \text{precision}) + \text{recall}}$$

Small β => prefer precision
Large β => prefer recall

Suggested adjust range
$0.1 < \beta < 2$

Prediction

		0	1
Ground Truth	0	TN	FP
	1	FN	TP

precision

recall

	precision	recall	f1-score	support
0	0.88	0.96	0.92	2011
1	0.73	0.45	0.56	489
avg / total	0.85	0.86	0.85	2500

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Before Advanced Feature Engineering

Function **f_beta_scann**

```
def f_beta_scann(y_true, y_pred, beta=0.5):
    """F beta score掃描找出最佳threshold"""

    y_pred = pd.Series(y_pred.ravel())
    # 切割100等分, 尋找最佳 f beta score
    bins = np.linspace(y_pred.min(), y_pred.max(), 100)
    # 找出F beta score最高的點
    result =
        np.array([
          precision_recall_fscore_support(
            y_true=y_true,
            y_pred=y_pred > thres, beta=beta)[2][1]
        for thres in bins])

    best_idx = result.argmax()
    return bins[best_idx], result[best_idx]
```

	0	1
precision		
Recall		
F score		$\boxed{}$
???		

Advanced Feature Engineering

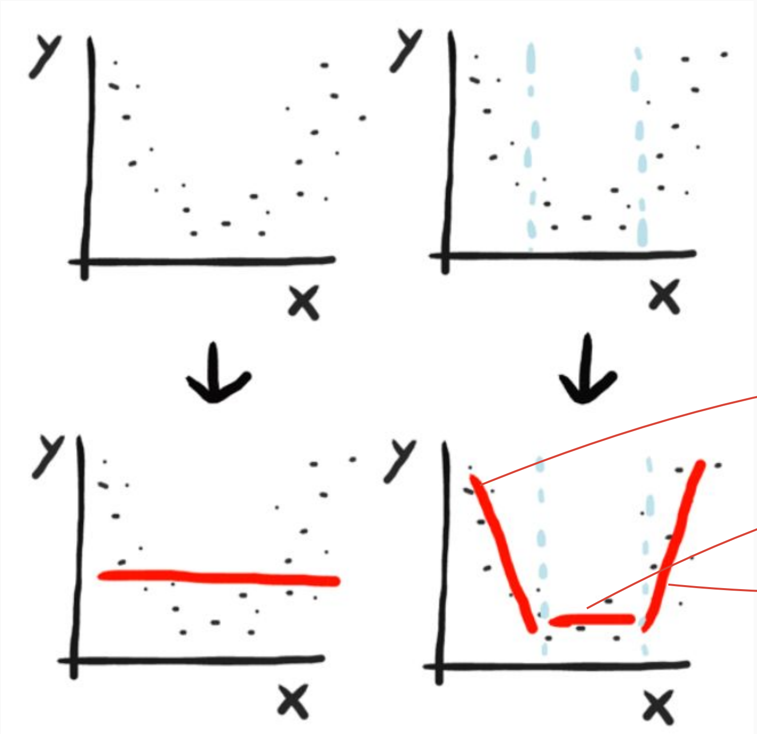
Advanced Feature Engineering

Coming up with features is difficult, time consuming, requires expert knowledge.
"**Applied machine learning**" is basically feature engineering.

-Andrew Ng

Advanced - Binning Numerical Variable

Binning ⇒ Find The Non-Linear Relationship



$$Y = WX + b$$

$$Y = W_1X_1 + W_2X_2 + W_3X_3 + b$$

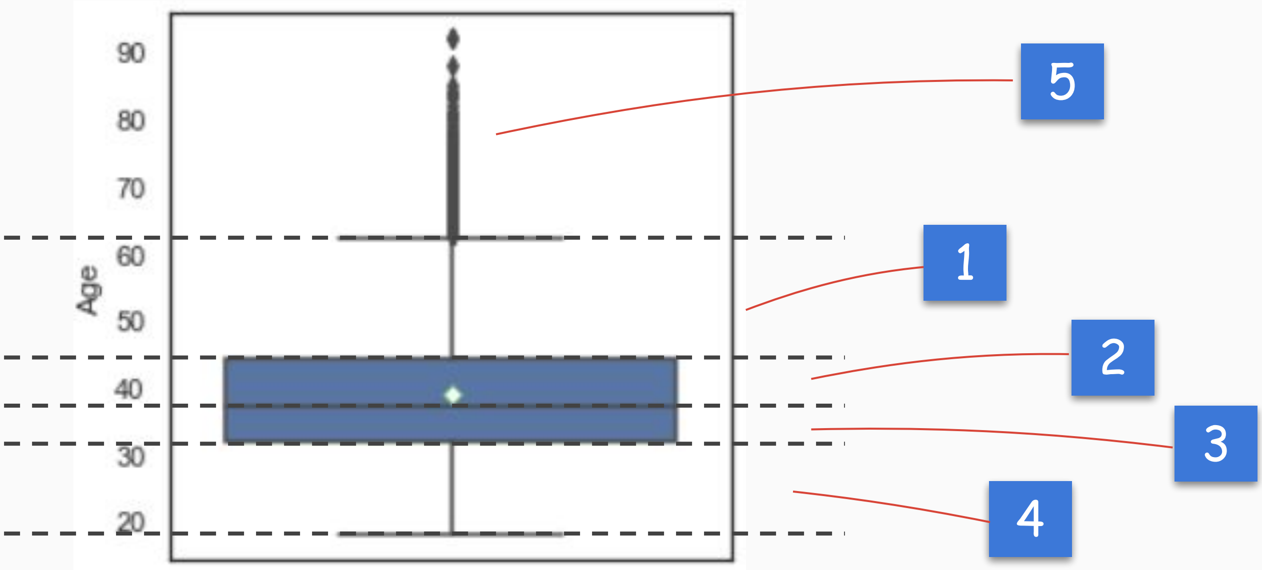
$$Y = W_1X_1 + \qquad + b$$

$$Y = \qquad W_2X_2 \qquad + b$$

$$Y = \qquad W_3X_3 + b$$

Advanced - Binning Numerical Variable

Binning Example ⇒ Quartile Cut



Advanced - Binning Numerical Variable

Binning Example ⇒ Quartile Cut

```
def quartile_binning(x):
    # Quartile cut
    bins = np.percentile(x, range(0, 100, 25))[1:].tolist()
    # IQR
    iqr_x_150 = (bins[-1] - bins[0]) * 1.5

    bins = [bins[0] - iqr_x_150] + bins + [bins[-1] + iqr_x_150]
            Lower bound                   Upper bound

    result = pd.Series(np.digitize(x, bins)) \
                .map(pd.Series([0, 1, 2, 3, 4, 0])).values
    return result, bins
```

Lab

Topic : Try Binning

Filename	lab_eda_insurance_claim.ipynb
Data	Financial Customer Churn Prediction
Target	Add binning features: ➔ Age, HasBalance, CreditScore, Tenure, EstimatedSalary
Duration	About 10 min

Advanced - WOE Encoding (Only for Binary Classification)

Weight of Evidence

Inspired from **Logistic Regression** ⇒ Binary Classification ⇒ 0 or 1

$$\sigma(wx + b) \qquad z = wx + b \qquad \boxed{\sigma = \frac{1}{1 + e^{-z}}}$$

LR function

Odds Ratio ⇒ $\dfrac{P}{1 - P}$

$$\frac{P}{1 - P} = \frac{\frac{1}{1+e^{-z}}}{1 - \frac{1}{1+e^{-z}}} = \ \dots \ = e^{z} = e^{wx+b} \Rightarrow log(\frac{P}{1 - P}) = wx + b$$

For the interpretable

Advanced - WOE Encoding (Only for Binary Classification)

Cancer Prediction Example ➡ $wx + b = 0.095 \cdot age + 2.645$

Log Odds Ratio $\log(\frac{P}{1-P}) = 0.095 \cdot age + 2.645$

Odds Ratio $e^{\log(\frac{P}{1-P})} = e^{0.095age+2.645} = e^{0.095age}e^{2.645}$

If age increase 1

$$e^{0.095(age+1)+2.645} = e^{0.095age}e^{0.095}e^{2.645}$$

(after increase) / (original)

$$\frac{e^{0.095age}e^{2.645}e^{0.095}}{e^{0.095age}e^{2.645}} = e^{0.095} = 1.099$$

When age increase 1, the odds ratio of having cancer increase 1.099

Advanced - WOE Encoding (Only for Binary Classification)

Weight of Evidence

$$WoE = \ln\left(\frac{\%\ non - events}{\%\ events}\right)$$

To avoid division by zero

$$WoE_{adj} = \ln\left(\frac{\text{Number of non-events in a group} + 0.5 \,/\, \text{Number of non-events}}{\text{Number of events in a group} + 0.5 \,/\, \text{Number of events}}\right)$$

Advanced - WOE Encoding (Only for Binary Classification)

Weight of Evidence

Feature	Outcome	WoE
A	1	0.4
A	0	0.4
A	1	0.4
A	1	0.4
B	1	0.74
B	1	0.74
B	0	0.74
C	1	-0.35
C	1	-0.35

	Non-events	Events	% of non-events	% of events	WoE
A	1	3	50	42	$\ln\left(\frac{(1+0.5)/2}{(3+0.5)/7}\right) = 0.4$
B	1	2	50	29	$\ln\left(\frac{(1+0.5)/2}{(2+0.5)/7}\right) = 0.74$
C	0	2	0	29	$\ln\left(\frac{(0+0.5)/2}{(2+0.5)/7}\right) = -0.35$

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Advanced - WOE Encoding (Only for Binary Classification)

Function **do_woe_encoding**

```python
total_vc = data[label].value_counts().sort_index()
def woe(pipe, total_vc):
    # Count by label in this group
    group_vc = pipe[label].value_counts().sort_index()

    # Some class in the feature is missing, fill zero to missing class
    if len(group_vc) < len(total_vc):
        for key in total_vc.index:
            if key not in group_vc:
                group_vc[key] = 0.
        group_vc = group_vc.sort_index()

    # WOE formula
    r = ((group_vc + 0.5) / total_vc).values

    # Odd ratio => 1 to 0, you can define meaning of each class
    return np.log(r[1] / r[0])

return data.groupby(x).apply(lambda pipe: woe(pipe, total_vc))
```

	Group dist	Global dist
0	0	2
1	2	7

Advanced - Target Encoding

Nominal Variable Frequency Encoding

Feature	Encoded Feature
A	0.44
A	0.44
A	0.44
A	0.44
B	0.33
B	0.33
B	0.33
C	0.22
C	0.22

A	0.44 (4 out of 9)
B	0.33 (3 out of 9)
C	0.22 (2 out of 9)

Advanced - Target Encoding

Nominal Variable Mean Encoding

Feature	Outcome	MeanEncode
A	1	0.75
A	0	0.75
A	1	0.75
A	1	0.75
B	1	0.66
B	1	0.66
B	0	0.66
C	1	1.00
C	1	1.00

A	0.75 (3 out of 4)
B	0.66 (2 out of 3)
C	1.00 (2 out of 2)

Lab

Topic : WOE + Target Encoding

Filename	lab_eda_insurance_claim.ipynb
Data	Financial Customer Churn Prediction
Target	➔ Add WOE Encoding Feature ➔ Add Target Encoding Feature
Duration	About 15 min

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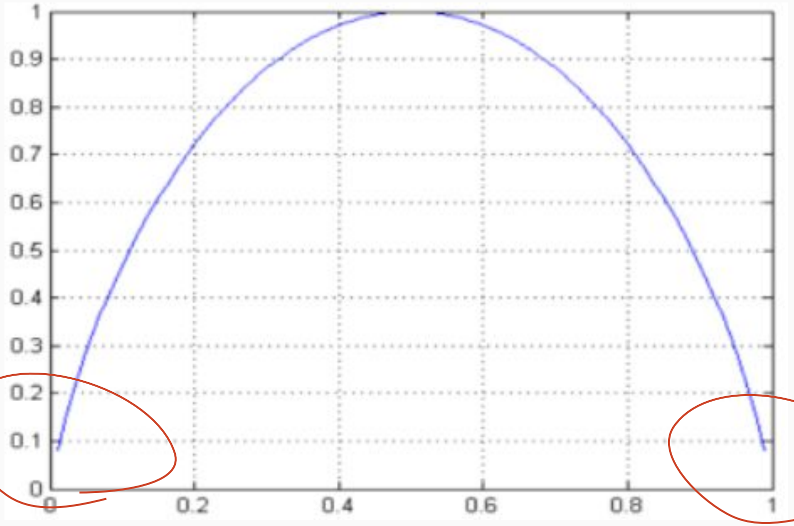
Advanced - Entropy Encoding

Entropy ⇒ Define the events first!

$$-\sum_i p_i \times log(p_i)$$

Lower entropy give more information !

Flip Coin Example



Advanced - Entropy Encoding

Entropy

Feature	Outcome
A	1
A	0
A	1
A	1
B	1
B	1
B	0
C	1
C	1

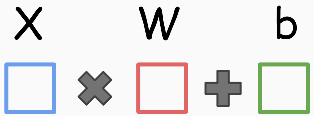
Evnet: 0, 1

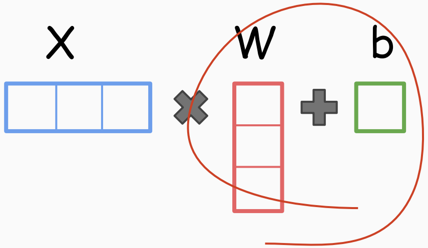
entropy(A) = - (1/4 x log(1/4) + 3/4 x log(3/4))
= 0.81
proba(A) = 4/9

=> result = 0.81 * 4/9 = 0.36

entropy(C) = -(1 x log(1)) = 0

Advanced - Polynomial Encoding

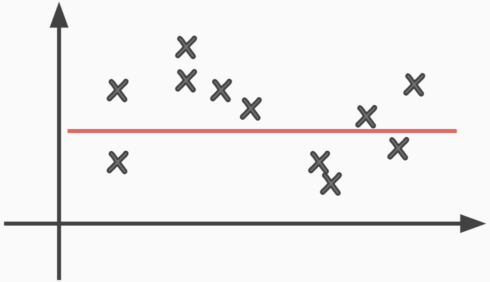




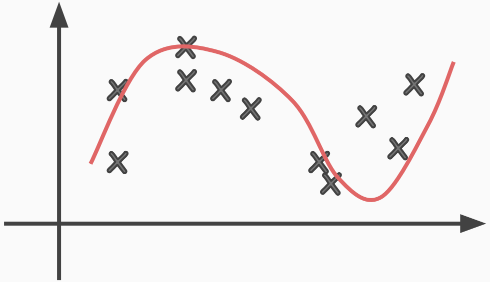

```python
from keras.layers import Dense

nets = Dense(units=64, ...)
nets = Dense(units=32, ...)
logits = Dense(units=1, ...)
```

$$Y = W_1X + b$$

$$Y = W_1X + W_2X^2 + W_2X^3 + b$$



Normal



Better fitting capability

[Tensorflow Playground]

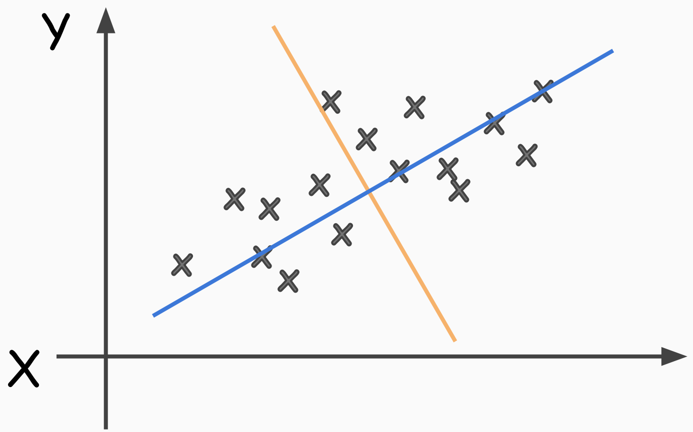
Lab

Topic : Entropy Encoding + Polynomial Encoding

Filename	lab_eda_insurance_claim.ipynb
Data	Financial Customer Churn Prediction
Target	➔ Add Entropy encoding ➔ Add Polynomial encoding
Duration	About 10 min

Advanced - PCA (Principal Component Analysis)

Sometimes we could face the curse of dimensionality

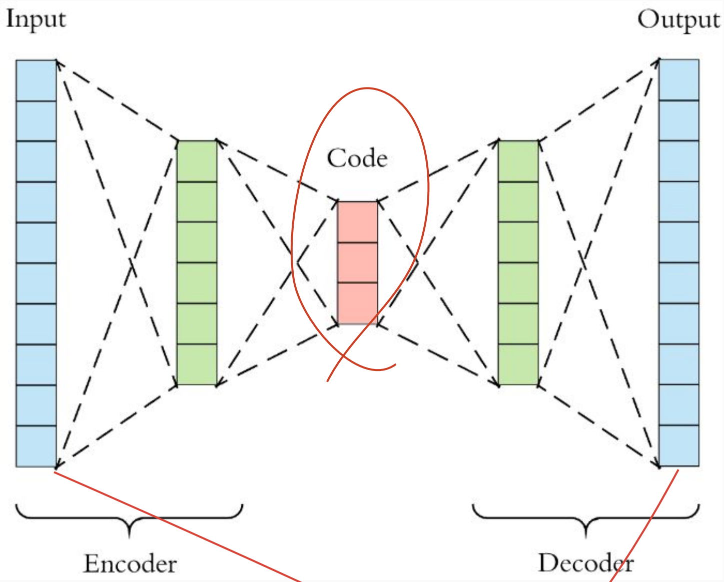


- Reduce the dimension of data
- Coordinate system transformation
- Mutually orthogonal axis
- Linear transformation

```python
from sklearn.decomposition import PCA

pca = PCA(32)
data = pca.fit_transform(data)
```

So simple ! thank god we have scikit learn

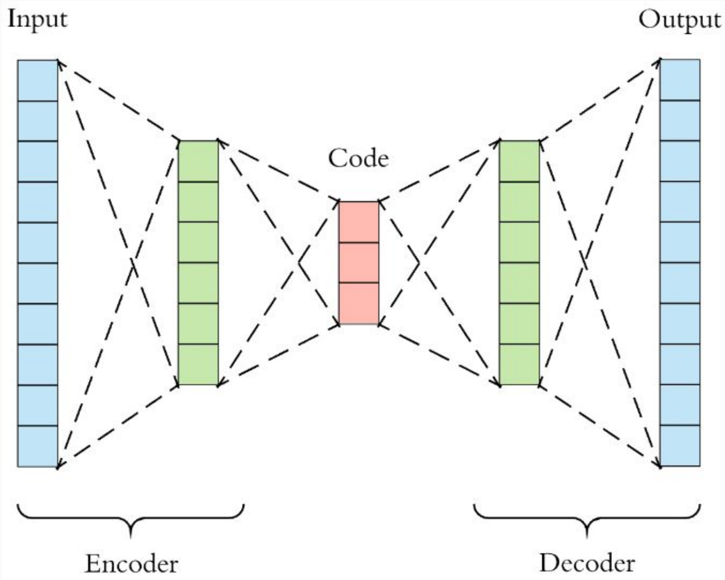
Advanced - AutoEncoder



Minimize Loss(input, output)

- Goal
  - Learn a specified data representation
  - Reduce the dimension of data
- Unsupervised learning
  - The input is the label
- Can be non-linear transformation
- The **"Code"** is what we want

Advanced - AutoEncoder



	AutoEncoder	PCA
Linear?	Non-linear	Linear
Dimension limitation	Non-limited	Less than input dimension

Advanced - AutoEncoder

```
inputs = Input(shape=(inputs_dim, ))
# Encoder
encoded = Dense(inputs_dim, activation='selu')(inputs)
encoded = Dense(128, activation='selu')(encoded)
encoded = Dense(64, activation='selu')(encoded)

encoded = Dense(64, activation='selu')(encoded)

# Decoder
decoded = Dense(64, activation='selu')(encoded)
decoded = Dense(128, activation='selu')(decoded)
decoded = Dense(inputs_dim, activation='linear')(decoded)

# this model maps an input to its reconstruction
autoencoder = Model(inputs, decoded)
# Adam Optimizer + Mean square error loss
autoencoder.compile(optimizer='adam', loss='mse')

# this model maps an input to its encoded representation
encoder = Model(inputs, encoded)
```

Coded

AutoEncoder model for training

Encoder model for prediction

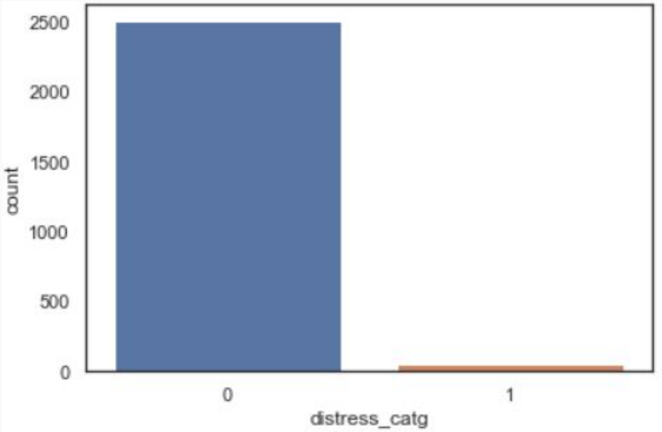
Lab

Topic : PCA Encoding + AutoEncoder Encoding

Filename	lab_eda_insurance_claim.ipynb
Data	Financial Customer Churn Prediction
Target	➔ Add PCA Encoding ➔ Add AutoEncoder Encoding
Duration	About 10 min

Advanced - Imbalanced Data For Classification

Majority Minority




```
class_weight: ...
    This can be useful to tell the model to
    "pay more attention" to samples from
    an under-represented class.
```

$$Loss = -\left(\underbrace{W * Y\log(\hat{Y})}_{\text{Minority}} + \underbrace{(1 - Y)\log(1-\hat{Y})}_{\text{Majority}} \right)$$

Minority : Majority = 1 : 40

class weights ⇒ {Minority : 40, Majority: 1}

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Advanced - RFM (Recency, Frequency, Monetary)

How recently, how often and how much did they buy.

Train

Company	rfm_all_freq	distress_num	rfm_all_mean
36	1	0.026703	0.026703
36	2	0.020268	0.023485
36	3	-0.046938	0.000011
36	4	-0.290000	-0.072492
36	5	-0.447700	-0.147533
36	6	-0.333620	-0.178548

Test

Company	rfm_all_freq	distress_num	rfm_all_mean
36	6	?	-0.178548
36	6	?	-0.178548
36	6	?	-0.178548

Beware the "Data leakage", label not in test data, so we take the RFM value from the last moment of train data

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Conclusion

- ➔ Domain knowlage is still the key of model performance
  ⇒ Why do you know RFM are good for transactional data?

- ➔ Deep learning can learning the feature transformation,
  but still got limitation

- ➔ Still need “a little” trial and error