Discrete Choice Model(Limited Depend Model)

Python Working Group Presentation 2018 Fall
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Presented in IAEE Conference 2015
Modified Version with ML approach

1 INTRO

DO WANT TO BUY PIZZA?

Decision = Simple Choice {0,1}

(example) 0 = buy pizza 1 = stay library
0 = Die 1= alive
0 = infected 1= not infected
0 = success 1= failure

Multiple Choice or {0,1,2,3,4}

(example) 0 = domino pizza 1 = Pizza Hut 2....

What factors(=X) will effect on Your Decision (=Y)

X1 = Income

X2 = Age

X3 = Weight

.
.
.
.

X = {X1, X2, X3…}

Y= $F(X)$ = W*X

$\xrightarrow{\quad\quad\quad}$

Mapping

Buying Pizza

Y={buy=1, otherwise=0}

INFERENCE : What factors causes your decision

$$Y = F(X) = W * X$$

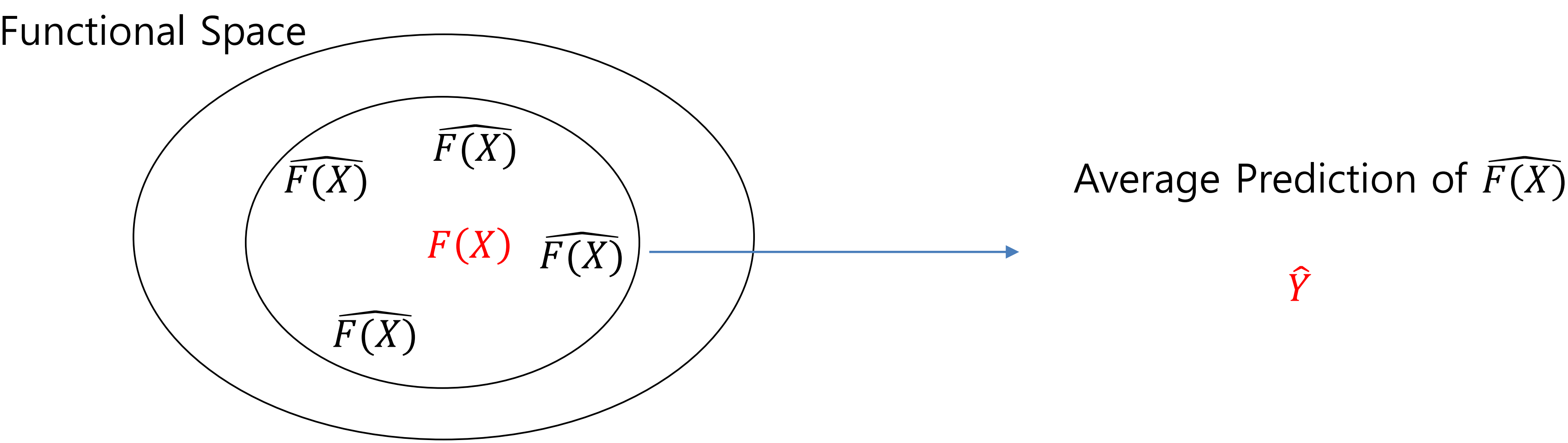
Discrete Choice Model = **Logistic Regression (Simple)**

$$\hat{Y} = F(X) = \hat{W} * X$$

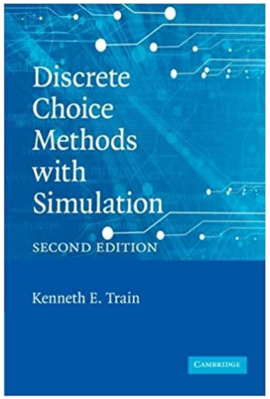
Prediction : Will make a decision or not

$$Y = F(X) = W^*X$$

Machine Learning



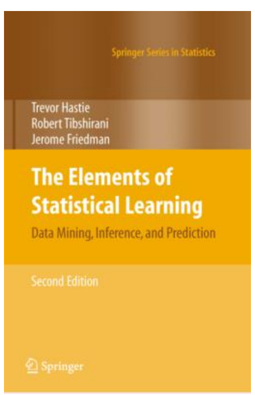
INFERENCE : Standard Logistic Regression



“Discrete Choice Methods With Simulation

PREDICTION : Logistic Regression

“The elements of statistical learning (ML approach in stat)



If time is allowable : Machine Learning

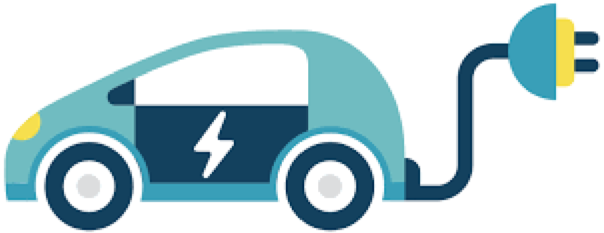
Random Forest + Bayesian Optimization
Ada Boosting + Bayesian Optimization

Research Example

"1. How to **apply**"
"2. Code for **LR**"
"3. **ML** approach"

Simple Example : Who buy Electric Vehicles and Why?

Decision : Buying EV =1
Not Buy EV = 0



For Coding, I made a Fake Data Set

Why we need electric vehicles?

National leaders have tried to find effective methods of **reducing both carbon emissions and the dependency on fossil fuels.**

Electric Vehicles (EVs) enable us to **reduce :**

① **Greenhouse gas emissions** in the transport sector,

② **Car operation costs** in times of high oil prices

③ Our **dependency** on **fossil fuels.**

Intro

EV Promotion in South Korea

GOAL

South Korean Government's goal :

① Producing **1.2 million** electric vehicles by **2015**

② Registering **1 million** electric vehicles by **2020.**

HOW

Subsiding EV :

① The Ministry of Environment is subsidizing EV purchases by approximately **$13,900**

② 10 major cities or provincial jurisdictions are providing additional subsidies, ranging from **$2,800 to $7,400**

Intro

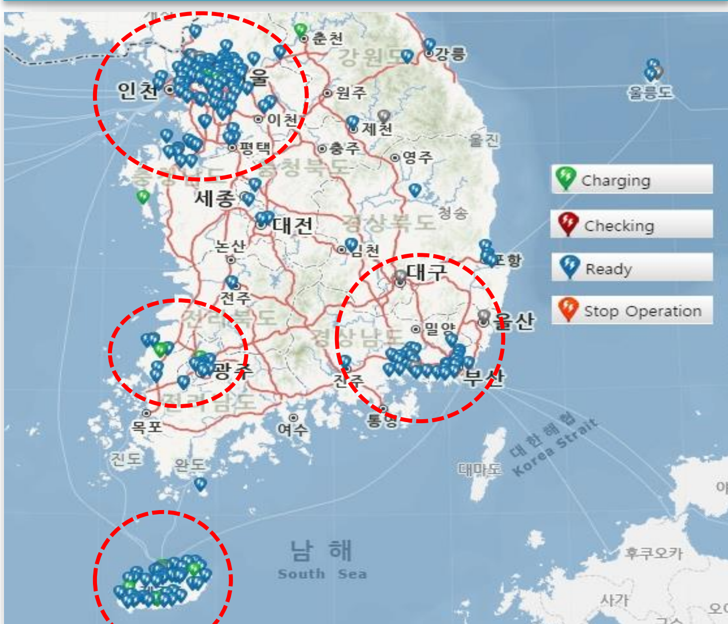
Current status deployment of Electric Vehicles (2015.5.8)

Very far from the goal (= 1 million EVs by 2020)

① Registered EV charging station : 227

② Electric vehicles users : **3,341**

Charging Station Monitor



Full of **BLUE** (= Ready for charging)

→ **Few EVs** to use charging

* Source : https://evcis.or.kr/com/egovMain.do

Research Question

The aim of this paper is to analyze Korean customers' willingness to buy EVs, for customers who have experienced riding in an EV

Data

The data stems from a survey conducted by the Korea energy Management Corporation over **October 1-31, 2013**

All respondents were **EV users** in either **Seoul or the Jeju region**, and the total number of respondents was 180;

excluding cases with incomplete response

the total sample data : **155**

Model Specification

Dependent Variable : Di you want to buy Electric Vehicle ?

Independent Variables : Age, Gender, Type of Job, Degree level, Service Group, Payment for Charging

Type		Name	Meanings	
Dependent		buy_moti1	Willingness to purchase electric vehicle among users	1 = yes 0= no
Age Group		age20s	Age groups in 20s	Dummy = 50s
		age30s	Age groups in 30s	Dummy = 50s
		age40s	Age groups in 40s	Dummy =50s
Sex		gender	Types of gender	Male = 1 Female = 0
Types of Job		job_student	Student	Dummy = Researcher
		job_office	Company employee	Dummy = Researcher
		job_public	Public servant	Dummy = Researcher
		job_speical	Specialist	Dummy = Researcher
Types of degree level		learn_ba	Graduated from undergraduate school	Dummy = High School
		learn_ma	Graduated from graduate school	Dummy = High School
Service Group		club_sharing	A member of Korea car sharing service	Dummy = EV users in Jeju
		club_kepco	A member of KEPCO EV car sharing service	Dummy = EV users in Jeju

Descriptive Statistics

All variable are dummy variable.

Variables	Obs	Mean	Std. Dev.	Min	Max
buy_moti1	155	.6258065	.4854826	0	1
age20s	155	.1483871	.3566356	0	1
age30s	155	.5096774	.5015268	0	1
age40s	155	.2709677	.4459002	0	1
gender	155	.7870968	.4106867	0	1
job_student	155	.0322581	.1772574	0	1
job_office	155	.4709677	.5007744	0	1
job_public	155	.3225806	.468979	0	1
job_speical	155	.0967742	.2966084	0	1
learn_ba	155	.6967742	.4611419	0	1
learn_ma	155	.2645161	.442505	0	1
club_sharing	155	.1870968	.3912533	0	1
club_kepco	155	.5096774	.5015268	0	1

Model Specification

Correlation

Weak correlation among independent variables in this study.

	age20s	age30s	age40s	gender	Job student	job_ office	Job_ public	job_ speical	learn_ba	learn_ma	club_ _sharing	club _kepco
age20s	1.0000											
age30s	-0.4256	1.0000										
age40s	-0.2545	-0.6216	1.0000									
gender	-0.0489	0.1835	-0.1084	1.0000								
job_student	0.2319	-0.0401	-0.1113	0.0950	1.0000							
job_office	0.0425	0.2274	-0.1681	0.3328	-0.1723	1.0000						
job_public	-0.1716	-0.3170	0.3556	-0.4840	-0.1260	-0.6511	1.0000					
job_speical	-0.0752	0.0591	-0.0523	0.0636	-0.0598	-0.3088	-0.2259	1.0000				
learn_ba	0.0779	-0.0855	-0.0084	-0.2402	-0.1179	-0.1087	0.3051	-0.0214	1.0000			
learn_ma	-0.0857	0.0615	0.0293	0.2404	0.1389	0.0495	-0.2887	0.0511	-0.9091	1.0000		
club_sharing	0.1720	0.0073	-0.1064	0.0879	0.0997	0.1108	-0.2957	0.0668	-0.1874	0.1249	1.0000	
club_kepco	-0.0262	0.3288	-0.2441	0.4357	0.0330	0.4342	-0.5379	0.0591	-0.1978	0.2371	-0.4891	1.0000

Discrete Choice Method and Other ML Techs(RF, Ada Boost)

Logit Model

Dependent variable in this study is binary which takes values 0 or 1

We use Logit regression which is a nonlinear regression model.

Logit models estimate the probability of dependent variable to be 1. It means the probability that some event happens.

$$\Pr(Y=1 \mid X1, X2, \ldots X_k) = F(\beta_0 + \beta_1 X1 + \beta_2 X2 + \ldots + \beta_K X_K)$$

$$\Pr(Y=1 \mid X1, X2, \ldots X_k) = \frac{1}{1+e^{-(\beta_0 + \beta_1 X1 + \beta_2 X2 + \ldots + \beta_K X_K)}}$$

$$\Pr(Y=1 \mid X1, X2, \ldots X_k) = \frac{1}{1+\left(\frac{1}{e^{(\beta_0 + \beta_1 X1 + \beta_2 X2 + \ldots + \beta_K X_K)}}\right)}$$

RESULT

2 INFERENCE

Model Specification

Empirical Result

Statistically, age group, types of job, service type have a influence on willingness to buy EVs

Variables	Coefficient	Standard Error	Z	P>|z|
age20s	-1.523536	1.080315	-1.41	0.158
Age30s***	-2.762704	.9795369	-2.82	0.005
Age40s	-1.170066	.8991289	-1.30	0.193
Gender	.2841433	.5364555	0.53	0.596
job_student*	-2.633748	1.355707	-1.94	0.052
job_office	.0201712	.743817	0.03	0.978
job_public	-.21472	1.025917	-0.21	0.834
job_speical*	2.230069	1.340147	1.66	0.096
learn_ba	.6843675	.9081867	0.75	0.451
learn_ma	.4114573	.972233	0.42	0.672
club_sharing**	1.989332	.9412754	2.11	0.035
club_kepco**	1.73136	.8339964	2.08	0.038
_cons	.5239554	1.649572	0.32	0.751
Log Likelihood	Number of Ob	LR chi2(2)	Prob > Chi2	PseudoR2
-84.584976	155	35.79	0.0004	0.1946

Empirical Result

Age	**30s** are **less** willing to buy EVs than **60s** (significant at 1%)
Job	**Students** show **less** willingness to buy EVs than **researchers** (significant at 10%)
	Specialist have a **higher** willingness to buy EVs than **researcher**s (significant at 10%)
Service Group	**The Korea car sharing service member** have a **higher** willingness to buy EVs than **EV users in Jeju** (significant at 5%)
	The KEPCO's EV car sharing service member have a higher willingness to buy EVs than **EV users in Jeju** (significant at 1%)

Marginal Effects

Marginal Effects show the change in probability when the predictor or independent variable increase by one unit.

Variables	dy/dx	Standard Error	Z	P>|z|
age20s	-.3368977	.2383876	-1.41	0.158
Age30s***	-.6109134	.2135531	-2.86	0.004
age40s	-.2587353	.1981022	-1.31	0.192
gender	.0628323	.1185	0.53	0.596
job_student*	-.5823977	.3026182	-1.92	0.054
job_office	.0044604	.1644718	0.03	0.978
job_public	-.0474808	.2271083	-0.21	0.834
job_speical*	.4931326	.2860709	1.72	0.085
learn_ba	.1513334	.2007506	0.75	0.451
learn_ma	.0909851	.2148848	0.42	0.672
club_sharing**	.4398986	.2052505	2.14	0.032
club_kepco**	.3828537	.1824838	2.10	0.036

Model Specification

Empirical Result

Age

The change in probability when age group goes from '50s' to '30s' decrease 61.09% is significant at 1%

Job

The change in probability when types of job goes from 'researcher' to 'job' decrease 58.2% is significant at 10%

The change in probability when types of job goes from 'researcher' to 'specialist' increase 49.3% is significant at 10%

Service Group

The change in probability when types of service group goes from 'EV users in Jeju ' to 'Car sharing service group' increase 43.98% is significant at 5%

- Korea Car Sharing service members live in Seoul

The change in probability when types of service group goes from 'EV user in Jeju group' to 'KEPCO EV car sharing service member' increase 38.28% is significant at 5%

- KEPCO EV car sharing service member live in Seoul

3 RESULTS AND IMPLICATION

Conclusion

Age group

- The reason people in their 30s are less willing to buy an EV may be due to their social status.
- In Korea, 30s need money for weddings, buying a house, and educating their children.
- 30s might have less room to pay for necessities.

☞ The government should provide greater subsidies that take customer's financial capacity to buy EVs into account.

Conclusion

Types of Job

- Researchers and specialist showed different attitudes to buying EVs.

☞ The high income level of specialist may be the reason for their greater willingness to buy compared to other groups.

- Researchers and student showed different attitudes to buying EVs.

☞ The low income level of student may be the reason for their lower willingness to buy compared to other groups.

Conclusion

Service Group

- Korea car sharing group members in Seoul have a higher willingness to buy EVs than EV user in Jeju.

- KEPCO car sharing group members in Seoul have a higher willingness to buy EVs than EV user in Jeju.

☞ Perhaps, there are regional differences in willingness to buy EVs

Conclusion

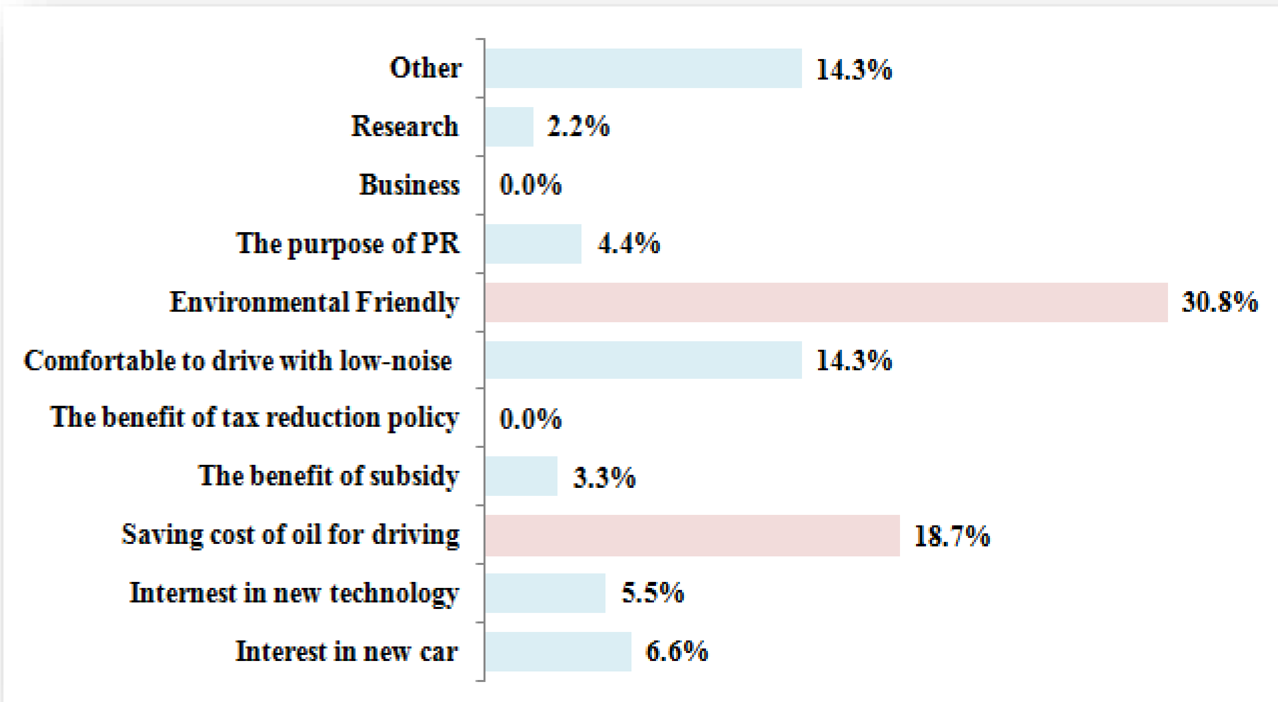
Service group

- The reason people in their 30s are less willing to buy an EV may be due to their social status.
- In Korea, 30s need money for weddings, buying a house, and educating their children.
- 30s might have less room to pay for necessities.
- ☞ Korean government should provide greater subsidies that take customer's financial capacity to buy EVs into account.

Conclusion

Specific motivation to buy EV among the respondent want to buy

- 91 out of 155 respondents answer that they want to buy EV.
- Environmental Friendly (30.8%) > Saving cost oil for driving (18.7%)
- ☞ We should consider those point when we make a market strategic for EV



Policy Implication for Korea

The evidence from this study suggests that policy makers should clearly understand customer's willingness to buy electric vehicle.

In this sense, policy makers should build up customized electricity-vehicle promotions based on their age group, types of job, service group, and region.

☞ In order to promote Evs, especially for EV users, Korea Government should consider **market segmentation** based on age, job, region.

Key Reference

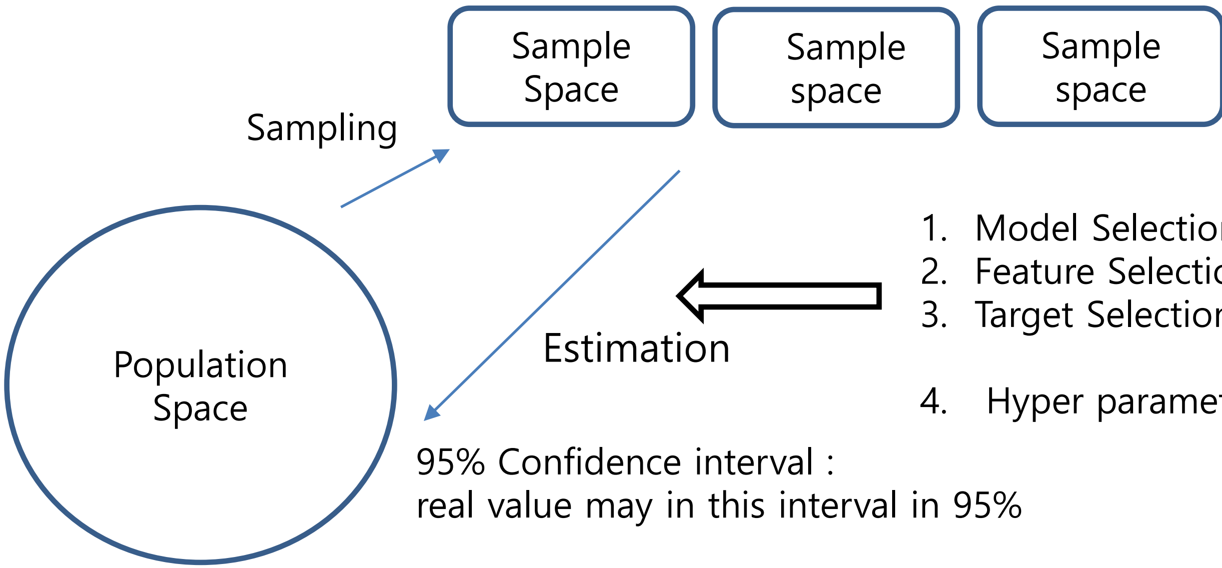
- Ona Egbue, Suzanna Long, Barriers to widespread adoption of electric vehicles: An analysis of customer attitude and perceptions, *Energy Policy*, Volume 48, 2012, Pages 717–729

- Alexander Kihm, Stefan Trommer, The new car market for electric vehicles and the potential for fuel substitution, *Energy Policy*, Volume 73, 2014, 147–157

- Korea Energy Management Corporation (KEMCO), EV demonstration project data analysis and EV distribution, *internal paper by KEMCO*, October

- 2013 Electric Vehicle News, Electric car sales set to take off in South Korea, April 18, 2014

Why



1. Model Selection : Ensemble (Bagging, Boost)
2. Feature Selection : Regularization
3. Target Selection : Ordered Probit, Structured prediction
4. Hyper parameter <u>Selection</u> : Bayesian Optimization

Discrete Choice Method and Other ML Techs(RF, Ada Boost)

Inference with **Logit Model (= Discrete Choice Model)**

Prediction with Logic Model (= Discrete Choice Model)
Random Forest (=ML, Bagging)
Ada Boost (=ML, Tree Based, Boosting)

$Y = F(x) = W * X$

1. Making Probability of Event = $P(Y=1|X)$

2. Making Odds Ratio = $\frac{P}{1-P}$

3. Making Objective Function which want to maximize

   -> Likelihood Function -> Log transformation -> Log-Likelihood Function

4. Finding Weight Vectors (= Coefficient in Stat)

   $\widehat{W}$ = argmax (Log-Likelihood Function)

5. Prediction With $\widehat{W}$ (Fitted from sample and predict with new sample X)

   Predicted Probability = $P(Y=1|X) = \widehat{W} * X$

Logistic Regression

Let's write $p(X) = \Pr(Y = 1|X)$ for short and consider using `balance` to predict `default`. Logistic regression uses the form

$$p(X) = \frac{e^{\beta_0+\beta_1 X}}{1 + e^{\beta_0+\beta_1 X}}.$$

$$S(x) = \frac{1}{1+e^{-x}} = \frac{e^x}{e^x+1}.$$

($e \approx 2.71828$ is a mathematical constant [Euler's number.])
It is easy to see that no matter what values β_0, β_1 or X take, $p(X)$ will have values between 0 and 1.

A bit of rearrangement gives

$$\log\left(\frac{p(X)}{1-p(X)}\right) = \beta_0 + \beta_1 X.$$

This monotone transformation is called the *log odds* or *logit* transformation of $p(X)$.

Reference : An Introduction to Statistical Learning, with Applications in R.

From : An Introduction to Statistical Learning, with Applications in R.

Maximum Likelihood

We use maximum likelihood to estimate the $\boxed{\text{parameters.}}$

$$\boxed{\ell(\beta_0, \beta) = \prod_{i:y_i=1} p(x_i) \prod_{i:y_i=0} (1 - p(x_i)).}$$

Joint pdf

This *likelihood* gives the probability of the observed zeros and ones in the data. We pick β_0 and β_1 to maximize the likelihood of the observed data.

⇨ Monotonic Transformation : Loglikelihood

$$\boxed{ll = \sum_{i=1}^{N} y_i \beta^T x_i - log(1 + e^{\beta^T x_i})}$$

Reference : The elements of statistical learning

$$
\begin{aligned}
\ell(\beta) &= \sum_{i=1}^{N} \left\{ y_i \log p(x_i;\beta) + (1-y_i)\log(1-p(x_i;\beta)) \right\} \\
&= \sum_{i=1}^{N} \left\{ y_i \beta^T x_i - \log(1+e^{\beta^T x_i}) \right\}. \qquad (4.20)
\end{aligned}
$$

Reference : The elements of statistical learning

$$\log\left(\frac{p(X)}{1-p(X)}\right) = \beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p$$

$$p(X) = \frac{e^{\beta_0+\beta_1 X_1+\cdots+\beta_p X_p}}{1+e^{\beta_0+\beta_1 X_1+\cdots+\beta_p X_p}}$$

$$\beta^{\text{new}} \leftarrow \arg\min_{\beta} (\mathbf{z}-\mathbf{X}\beta)^T \mathbf{W} (\mathbf{z}-\mathbf{X}\beta).$$

P = 0.5 >1
W*X(=Income, age) = Y = 0.6= 1 0.4 =0 0.3 =0

Reference : The elements of statistical learning

See the Code From Scracth

You can do it with **Sklearn,**
When you do prediction it is okay
When you do it for inference, you should check default setting
(Intercept, L2 regularization)

$$\begin{aligned} \ell(\beta) &= \sum_{i=1}^{N}\left\{y_i \log p(x_i;\beta) + (1-y_i)\log(1-p(x_i;\beta))\right\} \\ &= \sum_{i=1}^{N}\boxed{\left\{y_i\beta^T x_i - \log(1+e^{\beta^T x_i})\right\}.} \end{aligned} \tag{4.20}$$

Sklearn Default = Regularized likelihood Function, No intercept

$$\max_{\beta_0,\beta}\left\{\sum_{i=1}^{N}\left[y_i(\beta_0+\beta^T x_i) - \log(1+e^{\beta_0+\beta^T x_i})\right] - \lambda\sum_{j=1}^{p}|\beta_j|\right\}. \tag{4.31}$$

Coding from scratch and compare the results with Sklearn

https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html

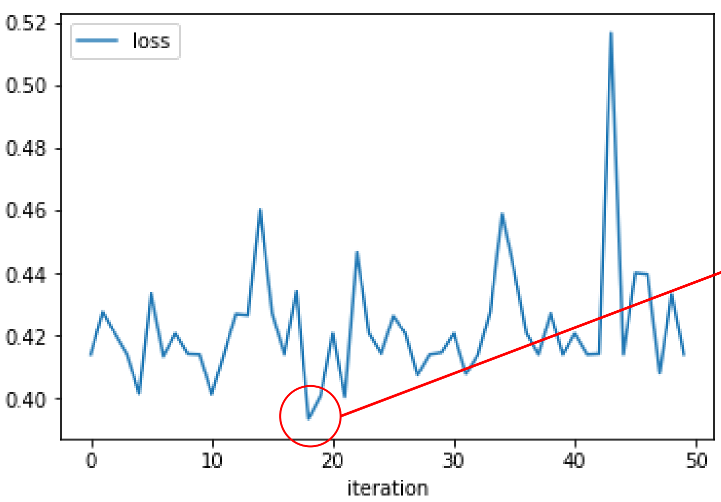
3. Prediction Compare it with ML **(Decision Tree Model)**

Boosting : Weak Estimator to Strong Estimator (No Noise, No Overfitting)
(Noise, Overfitting)

- XGBOOSTing is the cutting edge, but not much applicable for regression world
- Ada Boost is basic

Bagging : Random Forest <- **Injecting randomness** (Overfitting)

- **Parameter selection : Bayesian Optimazaiton (Hype OPT, SMAC, SPEAR)**



Start with P(D|X), your belief on distribution
See Observation, update belief, each iteration

Choose the hyperparameter
minimize the loss function

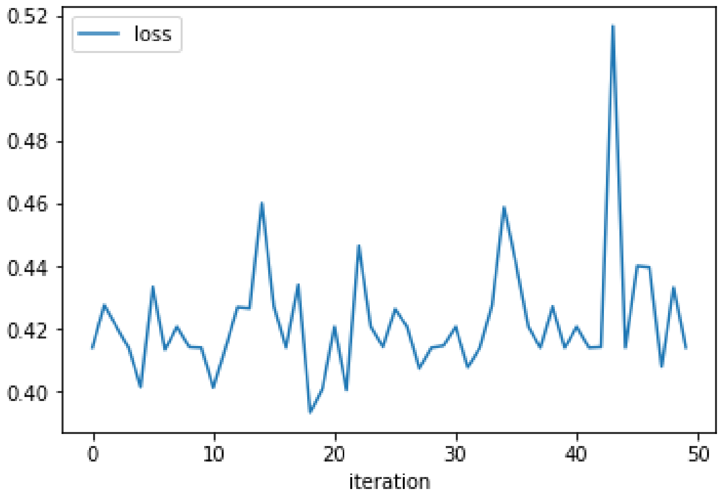
Loss function = 1- accuracy
Whatever you want to minize: OLS (MSE)

HyperOpt : Bayesian Optimization (Other Smac, Spear)

1. Setting Objective Function to Minimize (Ex, Loss, MSE, -Prediction Accuracy)

2. Set the Hyperparameter(Depth of Tree, Number of iteration)
   Space (Do main Space)

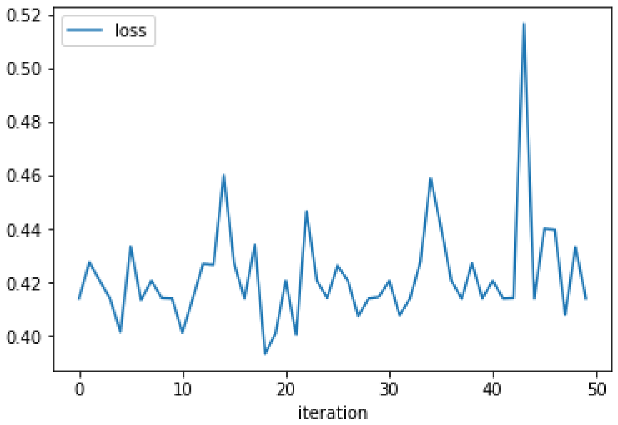
3. Optimize with iteration



Bayesian Optimization (Other Smac, Spear)

1. With Prior Belif P(D|X),

Logic P= P(Y=1|X)



2. See the actual observation

3. Update P(D'|X)

4. Repeat until converge

-> Decrease the number of parameter to estimate

Python Bayesian Optimization Modul :
https://conference.scipy.org/proceedings/scipy2013/pdfs/bergstra_hyperopt.pdf

2 PREDICTION

Prediction Accuracy between Discrete Choice vs ML

5 Fold Cross Validation Accuracy (Small Data Set = 155 sample size case)

Without Bayesian Optimization

Random Forest : 56%

Ada Boosting: 57%
(Decision Tree)

Binary Logistic: **60% (Win)**

Machine lose

With Bayesian Optimization

Random Forest : 59%

Ada Boosting**:** **63% (WIN)**
(Decision Tree)

Binary Logistic: 60%

Machine Win