Topics

GBDT

- ~~Code~~ for DecisionTrees ✓
- code for Random Forest ✓

HPT

- Boosting
  - Intuition ✓
  - Gradient Boosting
  - Bias-variance tradeoff.

[Adaboost]

- Math dive-deep (Post-read videos)

Business Problem + Data Proprocessing

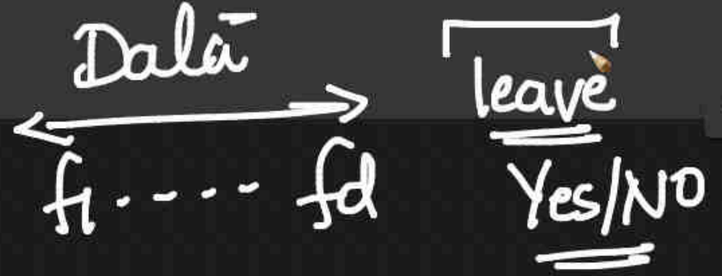

```
# HR/People Analytics
import numpy as np
import pandas as pd
import io
```

```
[ ] !wget "https://drive.google.com/uc?export=download&id=16KtxSt_QEGQvfluEaMls5cCHPwhRXgCk" -O HR-Employee-Attrition.c

--2022-05-13 13:24:44--  https://drive.google.com/uc?export=download&id=16KtxSt_QEGQvfluEaMls5cCHPwhRXgCk
Resolving drive.google.com (drive.google.com)... 142.250.141.113, 142.250.141.100, 142.250.141.139, ...
Connecting to drive.google.com (drive.google.com)|142.250.141.113|:443... connected.
HTTP request sent, awaiting response... 303 See Other
Location: https://doc-08-64-docs.googleusercontent.com/docs/securesc/ha0ro937gcuc717deffksulhg5h7mbp1/157t46bjk116kh
Warning: wildcards not supported in HTTP.
--2022-05-13 13:24:44--  https://doc-08-64-docs.googleusercontent.com/docs/securesc/ha0ro937gcuc717deffksulhg5h7mbp1
Resolving doc-08-64-docs.googleusercontent.com (doc-08-64-docs.googleusercontent.com)... 142.250.141.132, 2607:f8b0:
Connecting to doc-08-64-docs.googleusercontent.com (doc-08-64-docs.googleusercontent.com)|142.250.141.132|:443... co
HTTP request sent, awaiting response... 200 OK
Length: 227977 (223K) [text/csv]
Saving to: 'HR-Employee-Attrition.csv'

HR-Employee-Attriti 100%[===================>] 222.63K  --.-KB/s    in 0.009s
```

Business Problem + Data Proprocessing

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Resolving drive.google.com (drive.google.com)... 142.250.141.113, 142.250.141.100, 142.250.141.139, ...
Connecting to drive.google.com (drive.google.com)|142.250.141.113|:443... connected.
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Chrome File Edit View History Bookmarks Profiles Tab Window Help 9:07

DT and RF.ipynb - Colaborator | sklearn.tree.DecisionTreeClass | sklearn.ensemble.RandomFore

colab.research.google.com/drive/1d2HJ9AKulf83i7pwmDrL-2FOCncFubRF#scrollTo=DymQNKTQODL8

Update

+ Code + Text Reconnect

Business Problem + Data Proprocessing

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HR-Employee-Attriti 100%[===================>] 222.63K  --.-KB/s    in 0.009s
```

4 / 4

```
HR-Employee-Attriti 100%[===================>] 222.63K  --.-KB/s    in 0.009s

[105]
2022-05-13 13:24:44 (24.7 MB/s) - 'HR-Employee-Attrition.csv' saved [227977/227977]
```

```
df = pd.read_csv('HR-Employee-Attrition.csv')
df.head()
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	E
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	

5 rows × 35 columns

sch B M Ph2
1 2 3 4

```
[221] df = pd.read_csv('HR-Employee-Attrition.csv')
      df.head()
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	E
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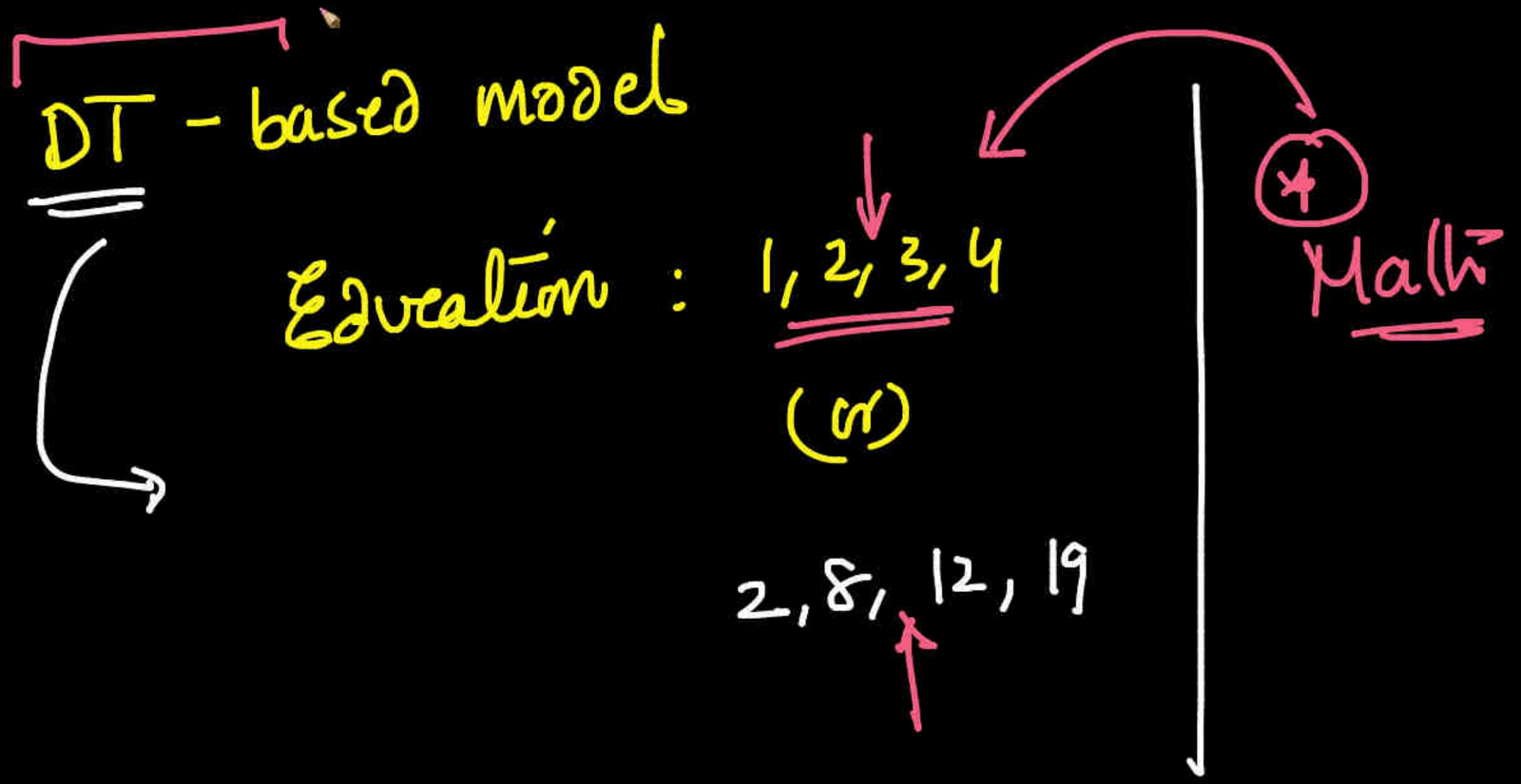
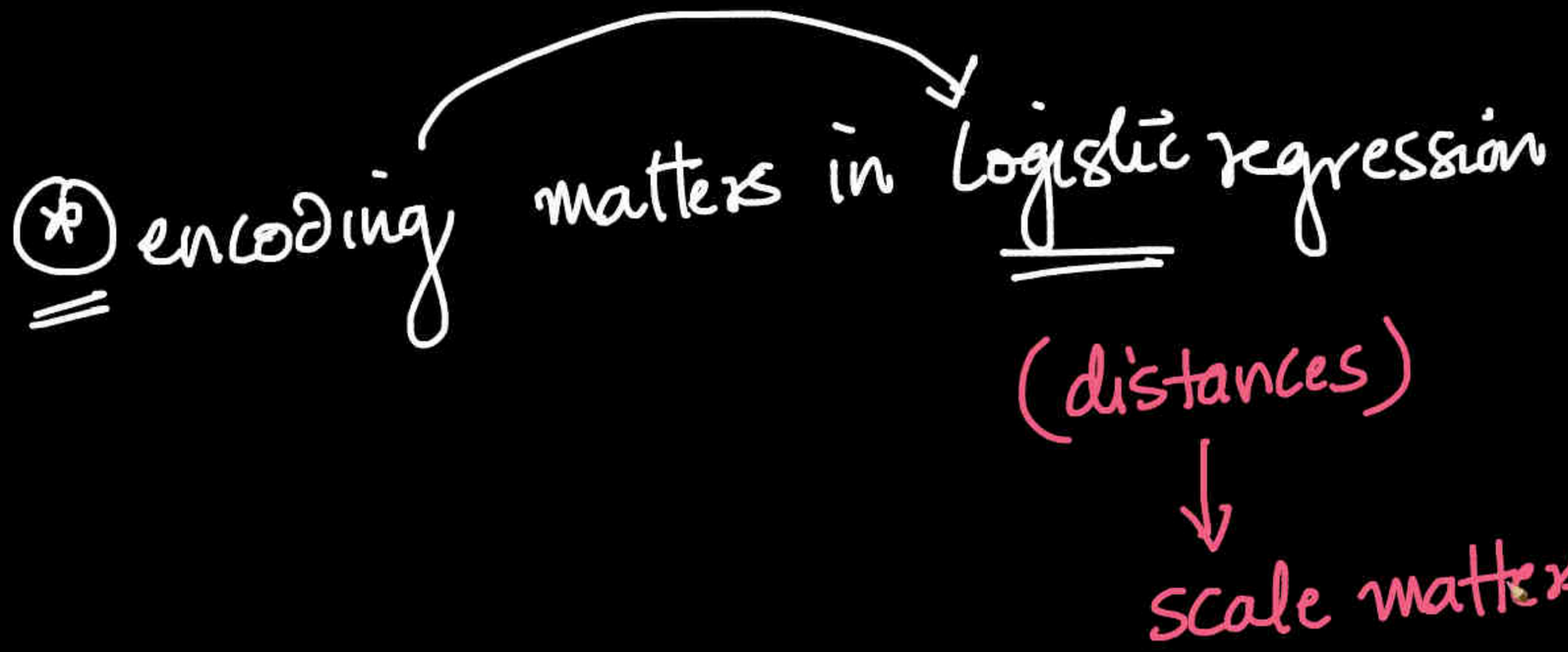
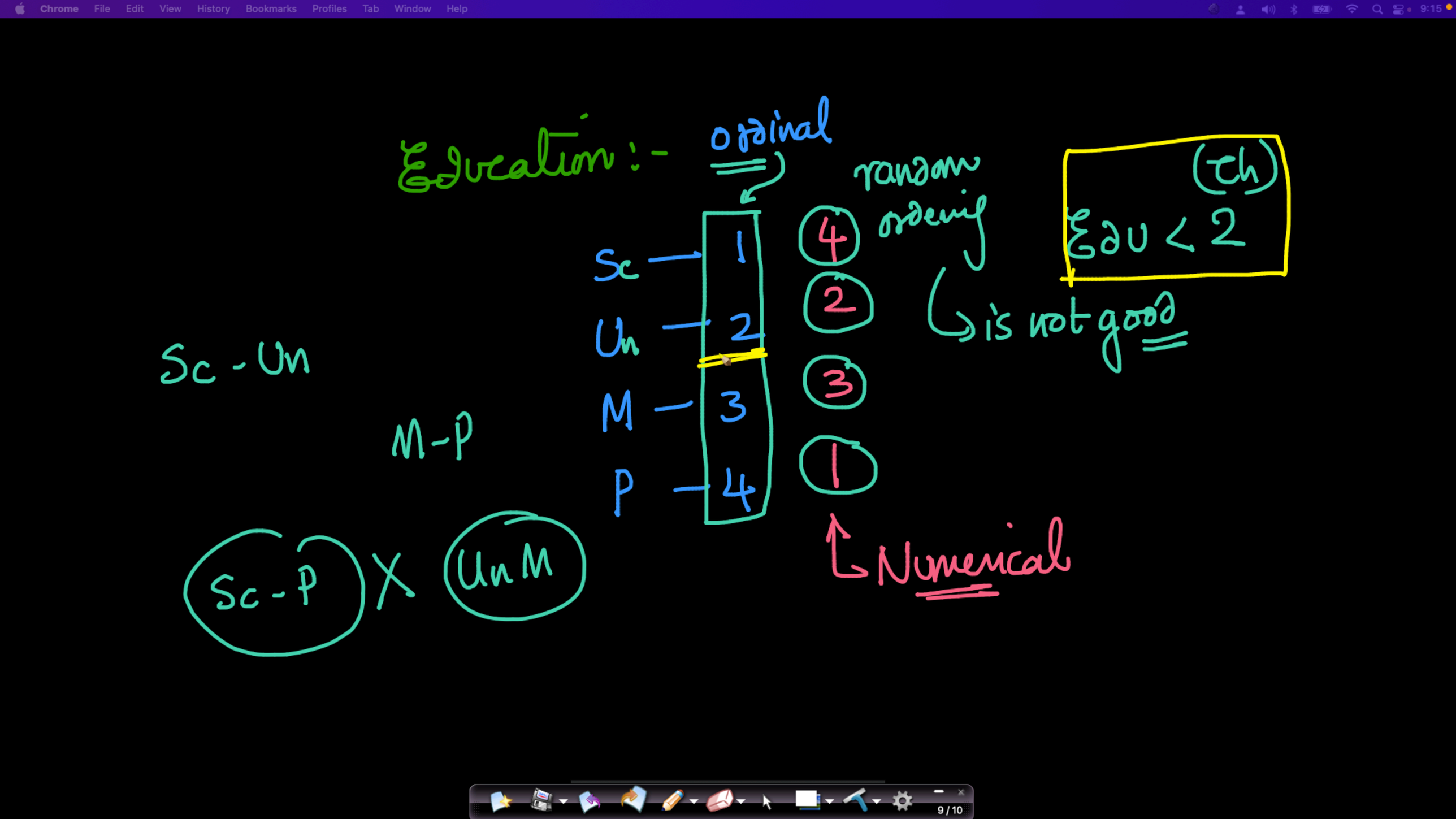
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	

5 rows × 35 columns

```
df.info()
```






Education :-
original
Sc
Un
M
P
1
2
3
4
random ordering
4
2
3
1
is not good
(th)
Edu < 2
Sc - Un
M - P
Sc - P
X
Un M
Numerical

Logistic regr

Education → OHE ✓

↳ Target Encoding ✓

```
 28  TotalWorkingYears         1470 non-null   int64
 29  TrainingTimesLastYear     1470 non-null   int64
 30  WorkLifeBalance           1470 non-null   int64
 31  YearsAtCompany            1470 non-null   int64
 32  YearsInCurrentRole        1470 non-null   int64
 33  YearsSinceLastPromotion   1470 non-null   int64
 34  YearsWithCurrManager      1470 non-null   int64
dtypes: int64(26), object(9)
memory usage: 402.1+ KB
```

[108]
```
# Business problems
# 1.Find employees who are at high risk of attrition and  take remedial steps [ML Model]
# 2. Identify factors leading to attrition [Feature importance]
```

[109]
```
# Data preprocessing

# y_i's as 1 and 0 instead of Yes and No
df['Attrition'].value_counts()
# imbalanced data (~1:6 ratio): Need to account for this while building ML models
```

```
No     1233
Yes     237
Name: Attrition, dtype: int64
```

```
 28  TotalWorkingYears         1470 non-null   int64
 29  TrainingTimesLastYear     1470 non-null   int64
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```

class-weights ; SMOTE ; ...

```
No     1233
Yes     237
Name: Attrition, dtype: int64
```

```
[110] df.loc[df['Attrition']=='Yes', 'Attrition'] = 1
      df.loc[df['Attrition']=='No', 'Attrition'] = 0
```

```
[111] df['Attrition'].value_counts()
```

```
0    1233
1     237
Name: Attrition, dtype: int64
```

```
# Data preprocessing

# y_i's as 1 and 0 instead of Yes and No
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No     1233
Yes     237
Name: Attrition, dtype: int64
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      df.loc[df['Attrition']=='No', 'Attrition'] = 0
```

```
[111] df['Attrition'].value_counts()
```

```
0    1233
1     237
Name: Attrition, dtype: int64
```

```
[112] # Sklearn DT doesnot handle categorical values natively.
      # Options: OHE or Target Encoding (our choice)
      # Converting all non numerical features into Target encoded features
```

[110] df.loc[df['Attrition']=='Yes', 'Attrition'] = 1
df.loc[df['Attrition']=='No', 'Attrition'] = 0

[111] df['Attrition'].value_counts()

```
0    1233
1     237
Name: Attrition, dtype: int64
```

[112] # Sklearn DT doesnot handle categorical values natively.
Options: OHE or Target Encoding (our choice)
Converting all non numerical features into Target encoded features

Q: Why not Label Encoding in Sklearn?

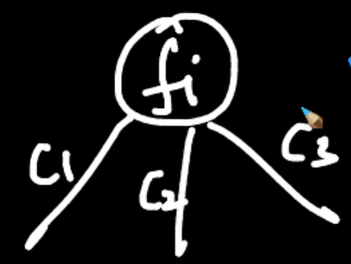
[113] !pip install category-encoders

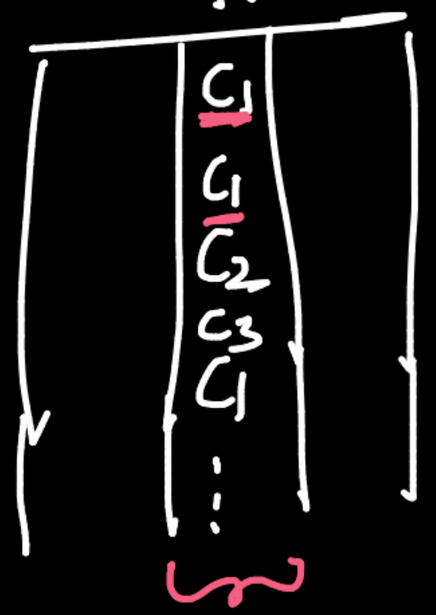
```
Requirement already satisfied: category-encoders in /usr/local/lib/python3.7/dist-packages (2.4.1)
Requirement already satisfied: scikit-learn>=0.20.0 in /usr/local/lib/python3.7/dist-packages (from category-encoder
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.7/dist-packages (from category-encoders) (1.2
Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.7/dist-packages (from category-encoders) (0.5.
Requirement already satisfied: statsmodels>=0.9.0 in /usr/local/lib/python3.7/dist-packages (from category-encoders)
```

open source

Can you fix this?

sklearn → cannot handles categorical features natively





→ DT

CART

R → DT

fi: Categorical-features for DT

↳ numeric

avoid → OHE → explode #features

if many categories → Target encoding $P(y_i=1 \mid f_i=c_1)$

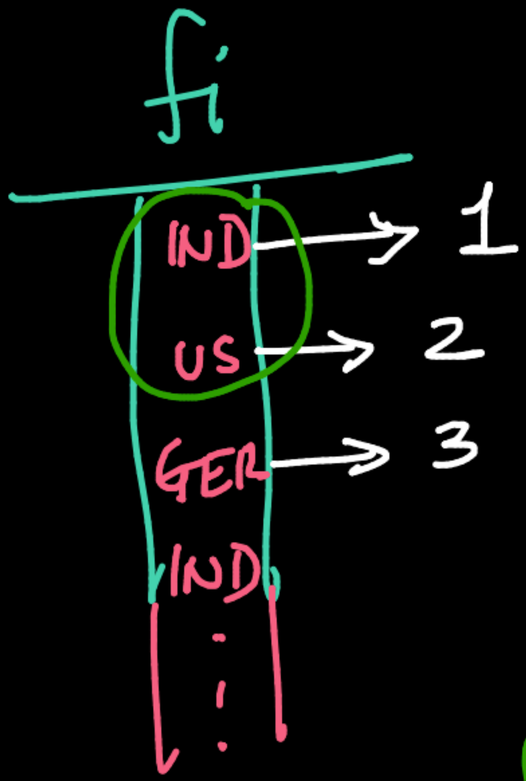
→ Label-encoding X

Label-encoding:-

Country: non-ordinal

creating random order

↳ random splits



randomly

$fi \leq 2$

sklearn.preprocessing.LabelEncoder

class sklearn.preprocessing.**LabelEncoder** [source]

Encode target labels with value between 0 and n_classes-1.

This transformer should be used to encode target values, *i.e.* `y`, and not the input `X`.

Read more in the User Guide.

New in version 0.12.

Attributes:

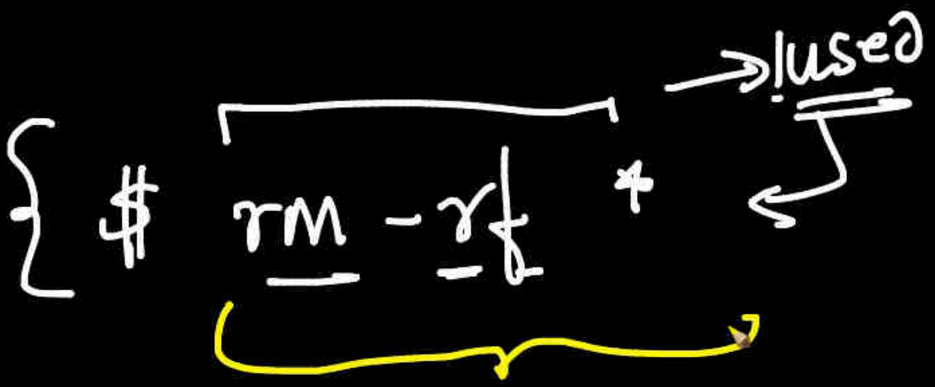
classes_ : *ndarray of shape (n_classes,)*
Holds the label for each class.

0
1
2

See also:

`OrdinalEncoder`
Encode categorical features using an ordinal encoding scheme.

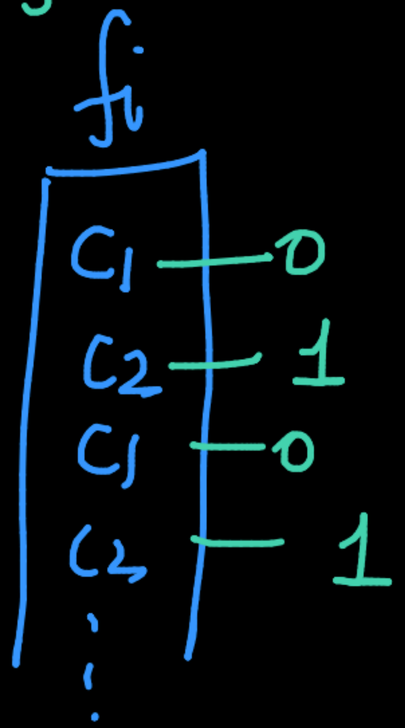
`OneHotEncoder`
Enco


{ # rm - r[ ] + 1 used

encode

5yxsvrndf → y_i → 0 / 1

label-encoding ✓



label-encoding can be done ..

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DT and RF.ipynb - Colaborator | sklearn.tree.DecisionTreeClass | sklearn.ensemble.RandomFore | sklearn.preprocessing.LabelEr

colab.research.google.com/drive/1d2HJ9AKulf83i7pwmDrL-2FOCncFubRF#scrollTo=Oa6CGasjdbd8

+ Code + Text

RAM Disk

```
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-packages (fro
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from patsy>=0.5.1->category-encoders)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.20.0->ca
```

[114]
```
from pandas.api.types import is_numeric_dtype
from category_encoders import TargetEncoder

# COnvert all non-nuemric fetures into Target-encoded features
HR_col = list(df.columns)
HR_col.remove('Attrition')
for col in HR_col:
  if is_numeric_dtype(df[col])== False:
    encoder = TargetEncoder()
    df[col] = encoder.fit_transform(df[col], df['Attrition'])
```

[115]
```
df.head()
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	E
0	41	1	0.149569	1102	0.206278	1	2	0.146865	1	
1	49	0	0.249097	279	0.138398	8	1	0.146865	1	

23 / 23

CE

fi

$c_1 \rightarrow$ 

$c_2 \rightarrow$ 

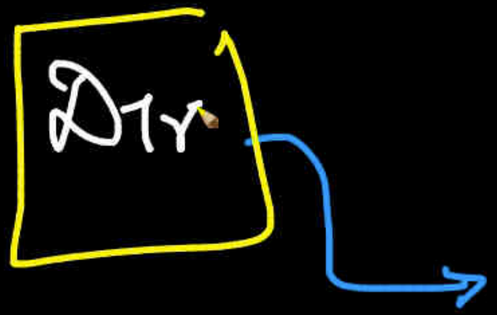
D → D_{TR} → Target Encoding ✓

D → D_{CV} ✓

D → D_{te} ✓

[no-leakage]

✓



f_i : C_1, C_2, C_3

$f_i : C_1 \rightarrow$ 0.15

$f_i : C_2 \rightarrow$ 0.60

$f_i : C_3 \rightarrow$ 0.02

D_{cv} or D_{te}

replace

$f_i : c_1 \rightarrow 0.15$

$f_i : c_2 \rightarrow 0.6$

$f_i : c_3 \rightarrow 0.02$

Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.20.0->ca

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colab.research.google.com/drive/1d2HJ9AKulf83i7pwmDrL-2FOCncFubRF#scrollTo=0kvclMDBL1HW

+ Code + Text

RAM
Disk

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```

```
BusinessTravel
Department
EducationField
Gender
JobRole
MaritalStatus
Over18
OverTime
```

— non-numeric

Educ: ordinal → numerical ✓

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[114] from pandas.api.types import is_numeric_dtype
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28 / 28

Chrome File Edit View History Bookmarks Profiles Tab Window Help 9:41

DT and RF.ipynb - Colaborator | sklearn.tree.DecisionTreeClass | sklearn.ensemble.RandomFore | sklearn.preprocessing.LabelEr

colab.research.google.com/drive/1d2HJ9AKulf83i7pwmDrL-2FOCncFubRF#scrollTo=0kvclMDBL1HW

Update

+ Code + Text

RAM
Disk

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Department
EducationField
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JobRole
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Over18
OverTime
```

D → Target encoding X

DTr ✓

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29 / 29

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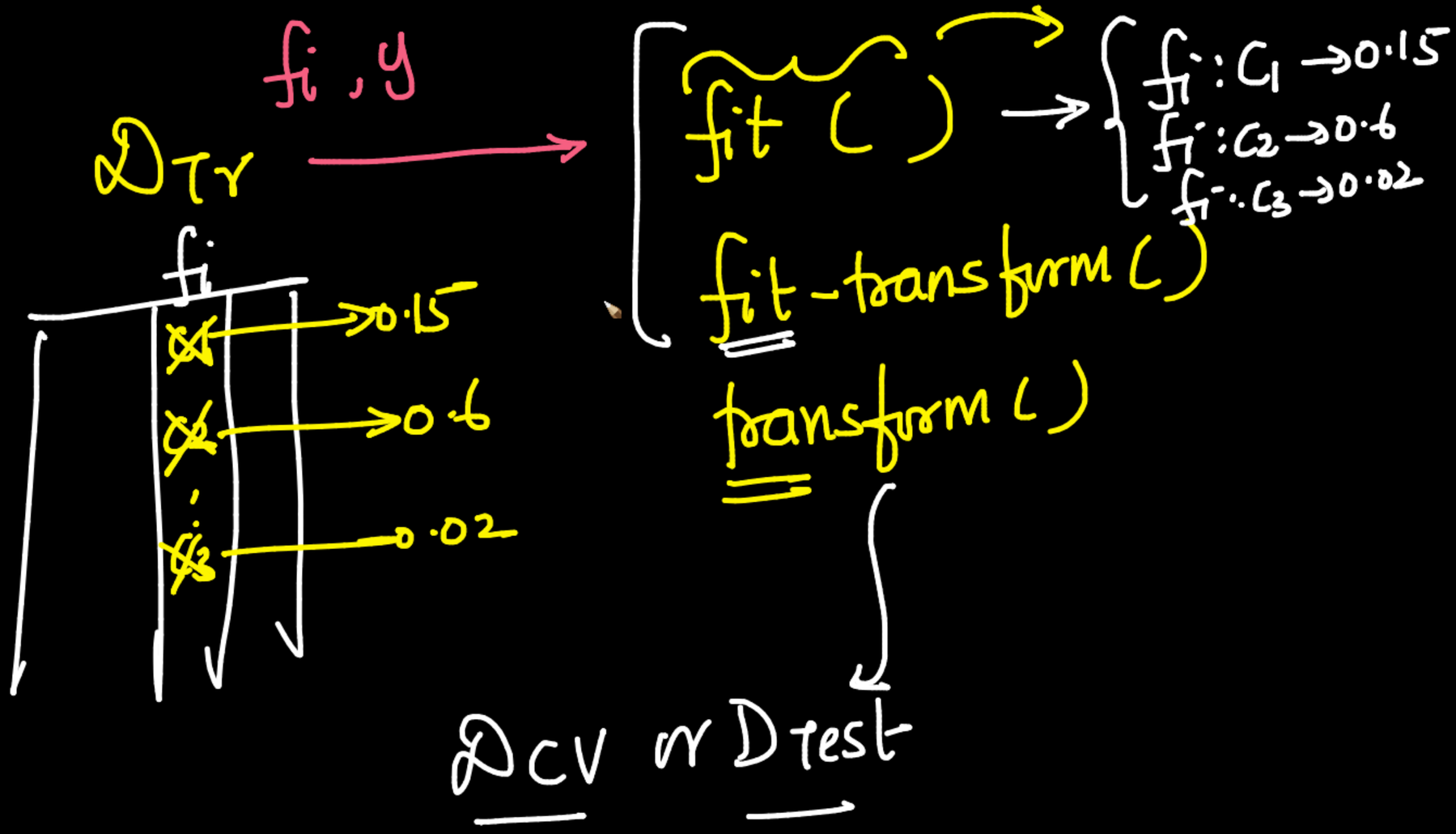

References

1

A Preprocessing Scheme for High-Cardinality Categorical Attributes in Classification and Prediction Problems, from

https://dl.acm.org/citation.cfm?id=507538

Methods

`fit` (X, y, **kwargs)	Fit encoder according to X and y.
`fit_transform` (X[, y])	Encoders that utilize the target must make sure that the traini
`get_feature_names` ()	Returns the names of all transformed / added columns.
`get_params` ([deep])	Get parameters for this estimator.
`set_params` (**params)	Set the parameters of this estimator.
`transform` (X[, y, override_return_df])	Perform the transformation to new categorical data.

fit_target_encoding	
target_encode	

`fit`(*X*, *y*, ***kwargs*) [source]

Fit encoder according to X and y.

```
from pandas.api.types import is_numeric_dtype
from category_encoders import TargetEncoder

# Convert all non-numeric features into Target-encoded features
HR_col = list(df.columns)
HR_col.remove('Attrition')
for col in HR_col:
  if is_numeric_dtype(df[col])== False:
    encoder = TargetEncoder()
    df[col] = encoder.fit_transform(df[col], df['Attrition'])
```

```
[115] df.head()
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	E
0	41	1	0.149569	1102	0.206278	1	2	0.146865	1	
1	49	0	0.249097	279	0.138398	8	1	0.146865	1	
2	37	1	0.149569	1373	0.138398	2	2	0.134146	1	
3	33	0	0.249097	1392	0.138398	3	4	0.146865	1	
4	27	0	0.149569	591	0.138398	2	1	0.135776	1	

```
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from category_encoders import TargetEncoder

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for col in HR_col:
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    df[col] = encoder.fit_transform(df[col], df['Attrition'])
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[115] df.head()
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3	33	0	0.249097	1392	0.138398	3	4	0.146865	1	
4	27	0	0.149569	591	0.138398	2	1	0.135776	1	

```
#Check if any non-numeric column exists in the DF
for col in HR_col:
  if is_numeric_dtype(df[col])== False:
    print(col)
```

```
[117] # Remove useless columns
      df['EmployeeNumber'].value_counts()
```

```
1       1
1391    1
1389    1
1387    1
1383    1
       ..
659     1
657     1
656     1
655     1
2068    1
Name: EmployeeNumber, Length: 1470, dtype: int64
```

```
[118] df['EmployeeCount'].value_counts()
```

```
1    1470
```

```
1          1
1391       1
1389       1
1387       1
1383       1
          ..
659        1
657        1
656        1
655        1
2068       1
Name: EmployeeNumber, Length: 1470, dtype: int64
```

```
df['EmployeeCount'].value_counts()
```

```
1    1470
Name: EmployeeCount, dtype: int64
```

```
[119] df['StandardHours'].value_counts()
```

```
80    1470
Name: StandardHours, dtype: int64
```

```
[120] df['Over18'].value_counts()
```

```
[118] df['EmployeeCount'].value_counts()
```

```
1    1470
Name: EmployeeCount, dtype: int64
```

```
[119] df['StandardHours'].value_counts()
```

```
80    1470
Name: StandardHours, dtype: int64
```


```
df['Over18'].value_counts()
```

```
0.161224    1470
Name: Over18, dtype: int64
```

```
[121] y = df['Attrition']
      y = y.astype('int')
```

```
[122] df.drop(['Attrition', 'EmployeeCount', 'EmployeeNumber',
               'StandardHours', 'Over18'], axis=1, inplace=True)
      print('Size of Full dataset is: {}'.format(df.shape))
```

```
[118] df['EmployeeCount'].value_counts()
```

```
1    1470
Name: EmployeeCount, dtype: int64
```

```
[119] df['StandardHours'].value_counts()
```

```
80    1470
Name: StandardHours, dtype: int64
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```
df['Over18'].value_counts()
```

```
0.161224    1470
Name: Over18, dtype: int64
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[121] y = df['Attrition']
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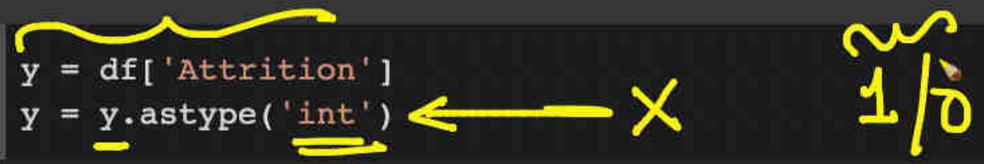
[122] df.drop(['Attrition', 'EmployeeCount', 'EmployeeNumber',
               'StandardHours', 'Over18'], axis=1, inplace=True)
      print('Size of Full dataset is: {}'.format(df.shape))
```

```
[120] df['Over18'].value_counts()

      0.161224    1470
      Name: Over18, dtype: int64
```

```
      y = df['Attrition']
      y = y.astype('int')
```




```
[122] df.drop(['Attrition', 'EmployeeCount', 'EmployeeNumber',
                'StandardHours', 'Over18'], axis=1, inplace=True)
      print('Size of Full dataset is: {}'.format(df.shape))

      X = df
```

```
      Size of Full dataset is: (1470, 30)
```

```
[123] # Train, CV, test split
      from sklearn.model_selection import train_test_split
      #0.6, 0.2, 0.2 split

      X_tr_cv, X_test, y_tr_cv, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

      X_train, X_val, y_train, y_val = train_test_split(X_tr_cv, y_tr_cv, test_size=0.25, random_state=42) # 0.25 x 0.8 =
```

```
df['Over18'].value_counts()
```

```
0.161224    1470
Name: Over18, dtype: int64
```

```
y = df['Attrition']
y = y.astype('int')
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df.drop(['Attrition', 'EmployeeCount', 'EmployeeNumber',
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X = df
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```
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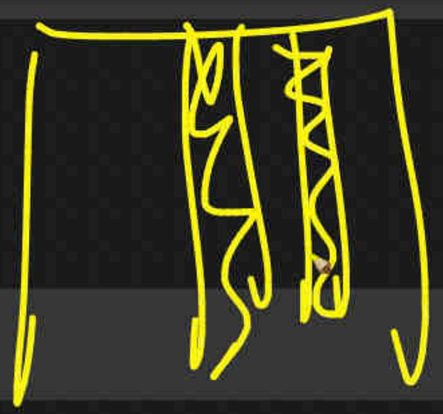

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```
[120] df['Over18'].value_counts()

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```

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      y = df['Attrition']
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```
[122] df.drop(['Attrition', 'EmployeeCount', 'EmployeeNumber',
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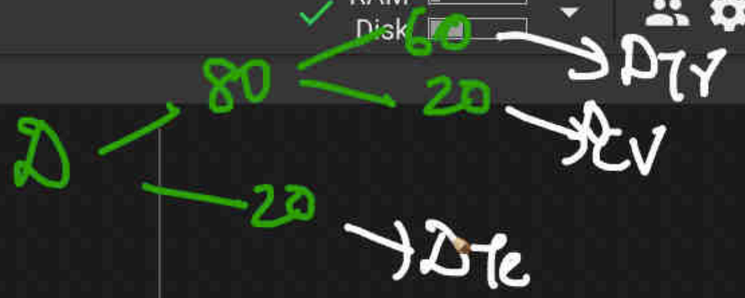

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```

[124]
```
print("Number transactions X_train dataset: ", X_train.shape)
print("Number transactions y_train dataset: ", y_train.shape)
print("Number transactions X_CV dataset: ", X_val.shape)
print("Number transactions y_CV dataset: ", y_val.shape)
print("Number transactions X_test dataset: ", X_test.shape)
print("Number transactions y_test dataset: ", y_test.shape)
```

```
Number transactions X_train dataset:  (882, 30)
Number transactions y_train dataset:  (882,)
Number transactions X_CV dataset:  (294, 30)
Number transactions y_CV dataset:  (294,)
Number transactions X_test dataset:  (294, 30)
Number transactions y_test dataset:  (294,)
```

Decision Trees

[123]
```
# Train, CV, test split
from sklearn.model_selection import train_test_split
#0.6, 0.2, 0.2 split

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```

[124]
```
print("Number transactions X_train dataset: ", X_train.shape)
print("Number transactions y_train dataset: ", y_train.shape)
print("Number transactions X_CV dataset: ", X_val.shape)
print("Number transactions y_CV dataset: ", y_val.shape)
print("Number transactions X_test dataset: ", X_test.shape)
print("Number transactions y_test dataset: ", y_test.shape)
```

```
Number transactions X_train dataset:  (882, 30)
Number transactions y_train dataset:  (882,)
Number transactions X_CV dataset:  (294, 30)
Number transactions y_CV dataset:  (294,)
Number transactions X_test dataset:  (294, 30)
Number transactions y_test dataset:  (294,)
```

Decision Trees

```
# Hyper-pram tuning + DT model
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import f1_score

train_scores = []
val_scores = []

l=1
u=20
d=1
w=1.0

for depth in np.arange(l,u,d):
  clf = DecisionTreeClassifier(random_state=0, max_depth=depth, class_weight={ 0:0.1, 1:w } )
  clf.fit(X_train, y_train)
  train_y_pred = clf.predict(X_train)
  val_y_pred = clf.predict(X_val)
  train_score = f1_score(y_train, train_y_pred)
  val_score = f1_score(y_val, val_y_pred)
  train_scores.append(train_score)
  val_scores.append(val_score)
```

```
[209] import matplotlib.pyplot as plt
```

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  clf.fit(X_train, y_train)
  train_y_pred = clf.predict(X_train)
  val_y_pred = clf.predict(X_val)
  train_score = f1_score(y_train, train_y_pred)
  val_score = f1_score(y_val, val_y_pred)
  train_scores.append(train_score)
  val_scores.append(val_score)
```

1,2,3,4, . . . 20

1 → 20

```
[209] import matplotlib.pyplot as plt
```

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  train_score = f1_score(y_train, train_y_pred)
  val_score = f1_score(y_val, val_y_pred)
  train_scores.append(train_score)
  val_scores.append(val_score)
```

depth = 1, 2, ... 20

1:1

1:10

hyper-param

1:0

```
[209] import matplotlib.pyplot as plt
```

Combinations

depth = 1

depth = 1

"

depth = 2

"

Class weights : 0.1 : 0.6

" : 0.1 : 1.0

" : 0.1 : 2.0

"

C.W = 0.1 : 0.6

0.1 : 1.0

"

⋮

⋮

GBDT → automate

GridSearch
RandomSearch

on HP

```
l=1
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  val_y_pred = clf.predict(X_val)
  train_score = f1_score(y_train, train_y_pred)
  val_score = f1_score(y_val, val_y_pred)
  train_scores.append(train_score)
  val_scores.append(val_score)
```

tunable

[209]
```
import matplotlib.pyplot as plt

plt.figure()
plt.plot(list(np.arange(l,u,d)), train_scores, label="train")
plt.plot(list(np.arange(l,u,d)), val_scores, label="val")
plt.legend(loc='lower right')
plt.xlabel("lambda")
plt.ylabel("F1-Score")
plt.grid()
```

```
l=1
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for depth in np.arange(l,u,d):
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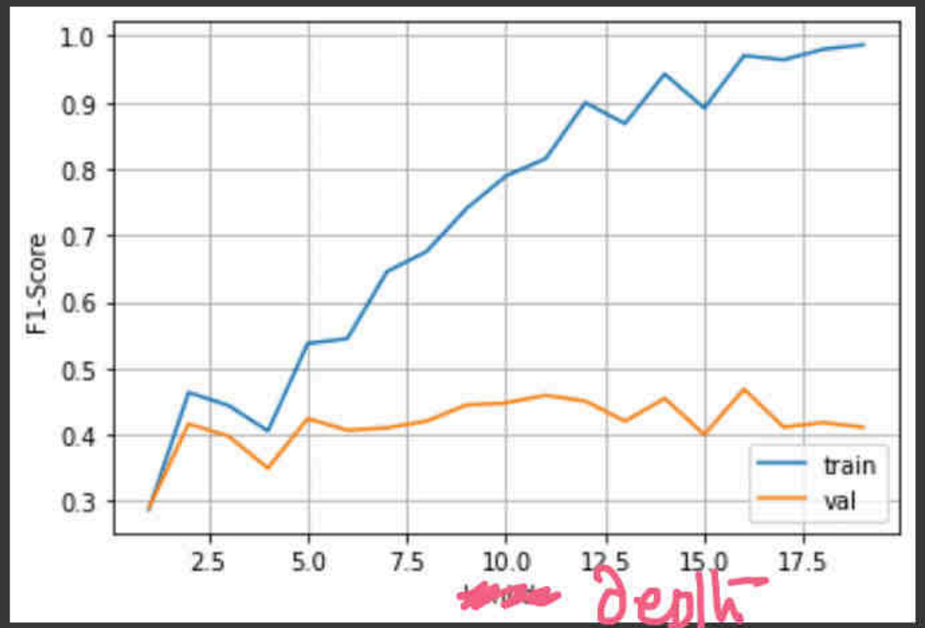
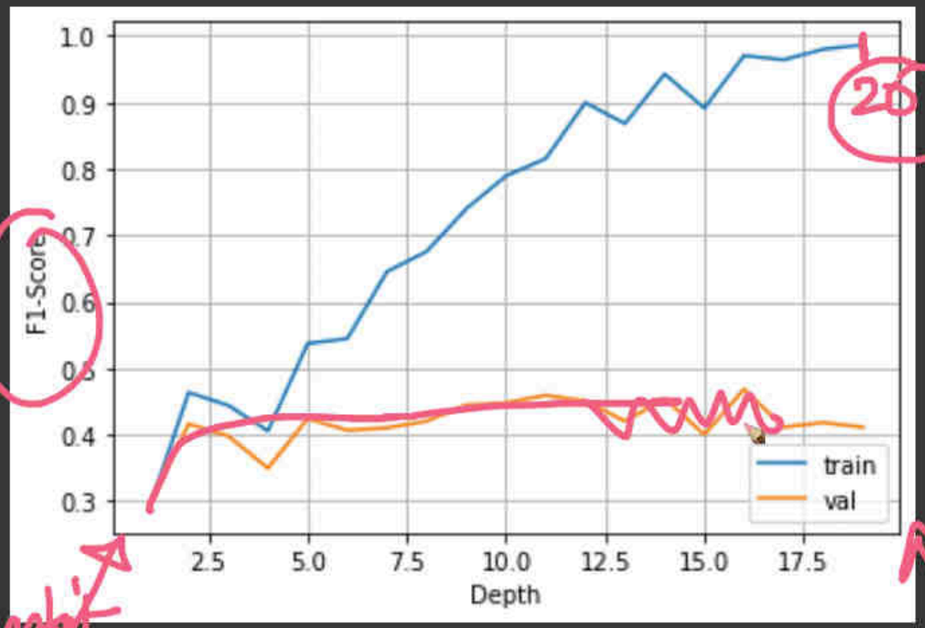
plt.xlabel("lambda")
plt.ylabel("F1-Score")
plt.grid()
plt.show()
```




```
[210] # Model with depth_best
      from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score, f1_score, precision_re

      best_idx = np.argmax(val_scores)
```

```
plt.plot(list(np.arange(1,u,d)), val_scores, label="val")
plt.legend(loc='lower right')
plt.xlabel("Depth")
plt.ylabel("F1-Score")
plt.grid()
plt.show()
```



800 train pts 30 feat

20

underfit

overfit

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plt.plot(list(np.arange(l,u,d)), val_scores, label="val")
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plt.xlabel("Depth")
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plt.grid()
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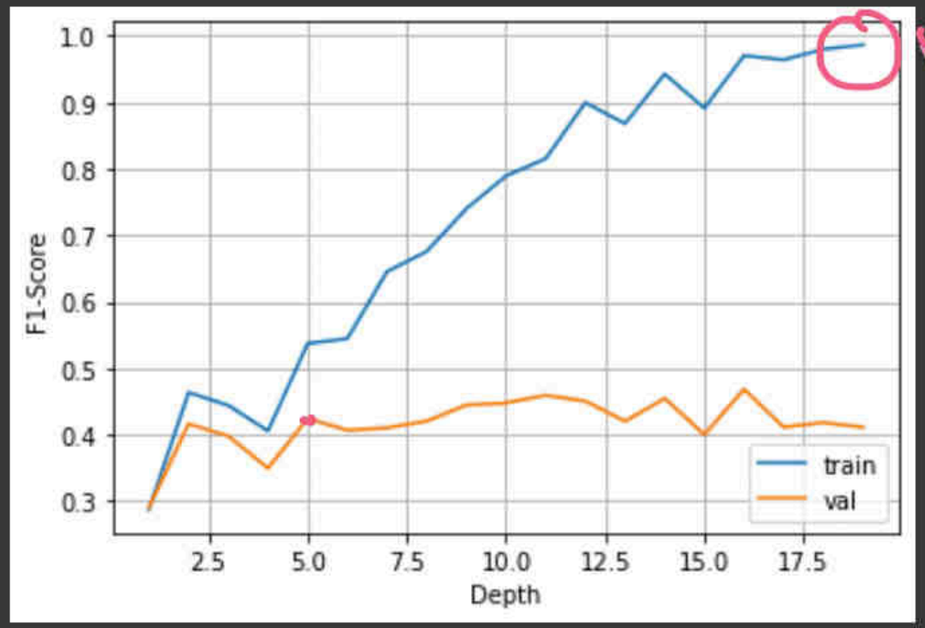
```

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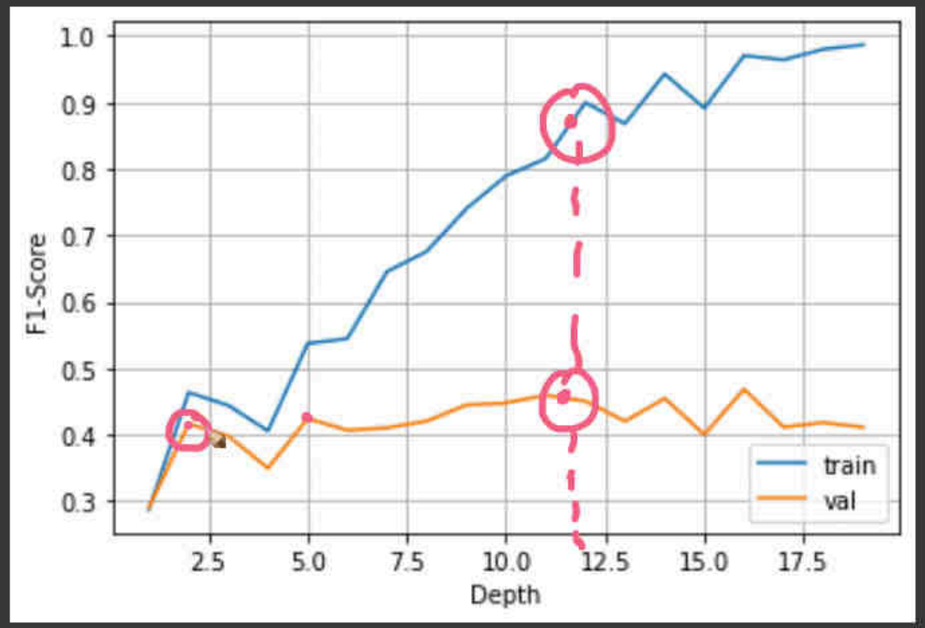


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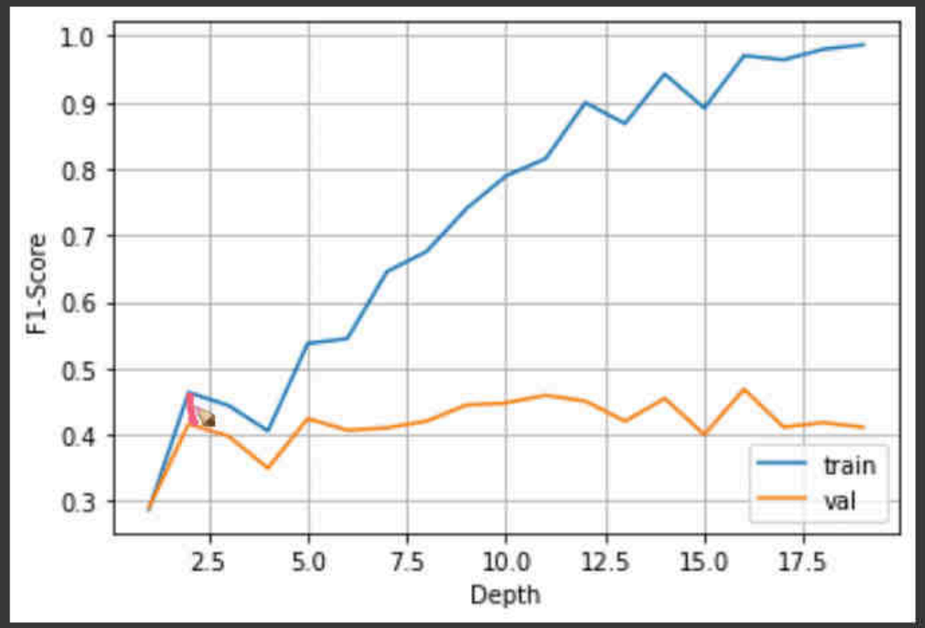


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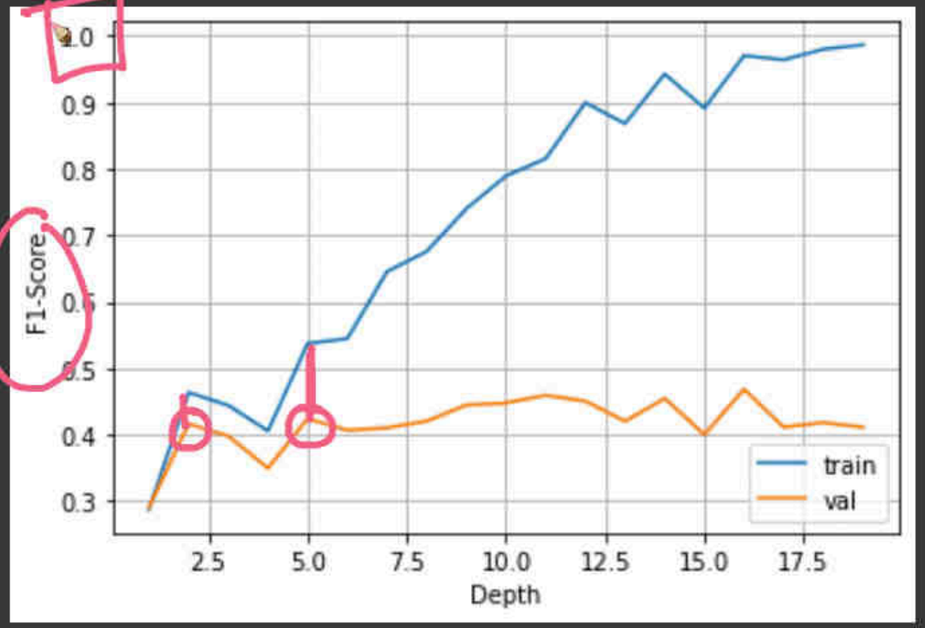


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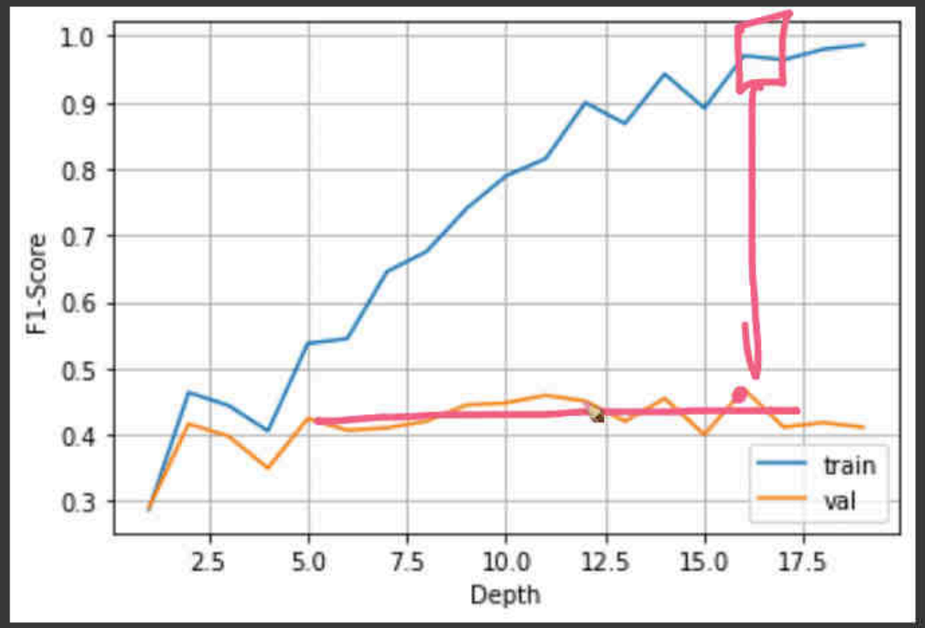
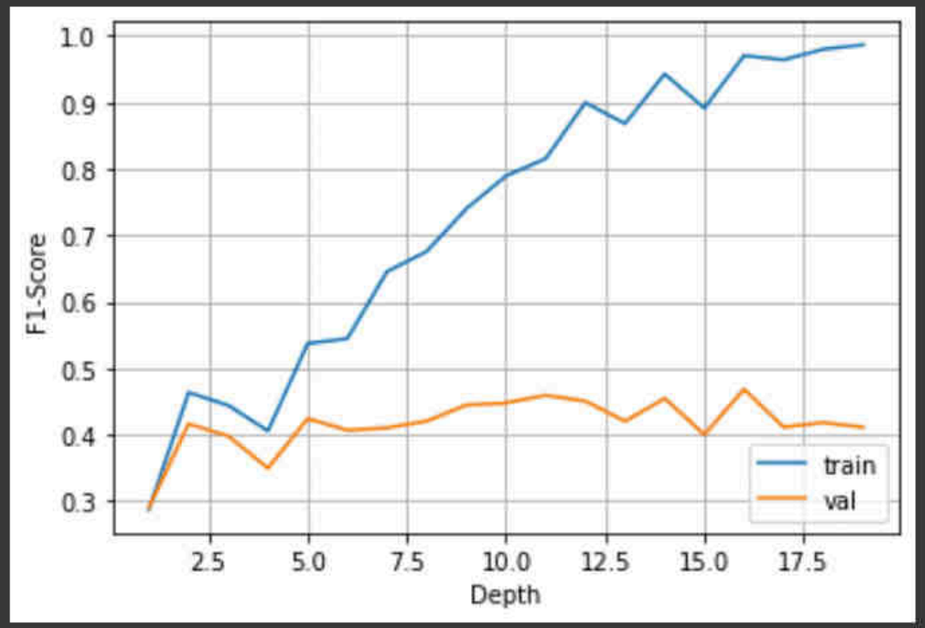
```




```
[210] # Model with depth_best
      from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score, f1_score, precision_re

      best_idx = np.argmax(val_scores)
```

```
plt.plot(list(np.arange(1,u,d)), val_scores, label="val")
plt.legend(loc='lower right')
plt.xlabel("Depth")
plt.ylabel("F1-Score")
plt.grid()
plt.show()
```

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[210] # Model with depth_best
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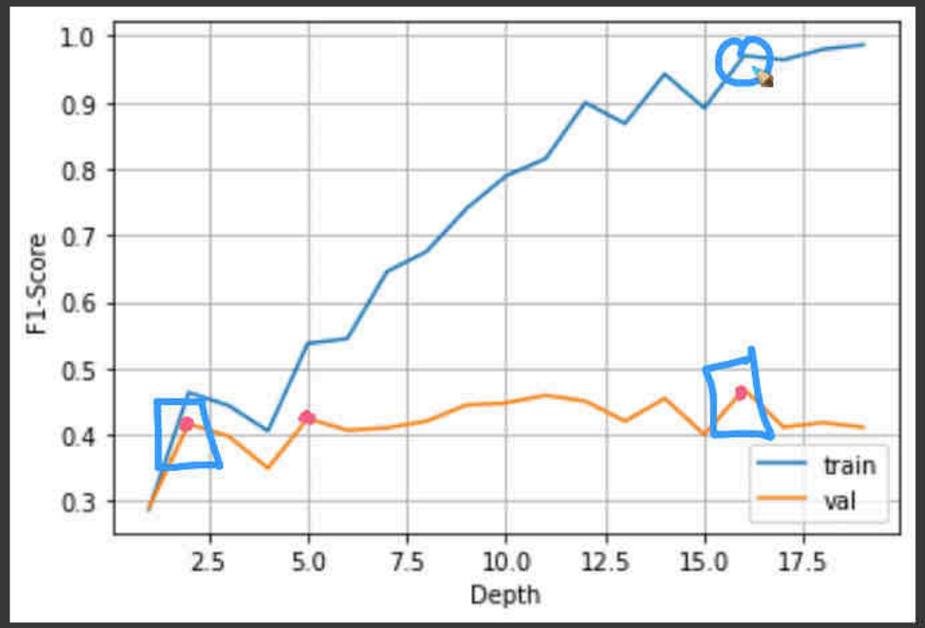
```



800

```
[210] # Model with depth_best
      from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score, f1_score, precision_re

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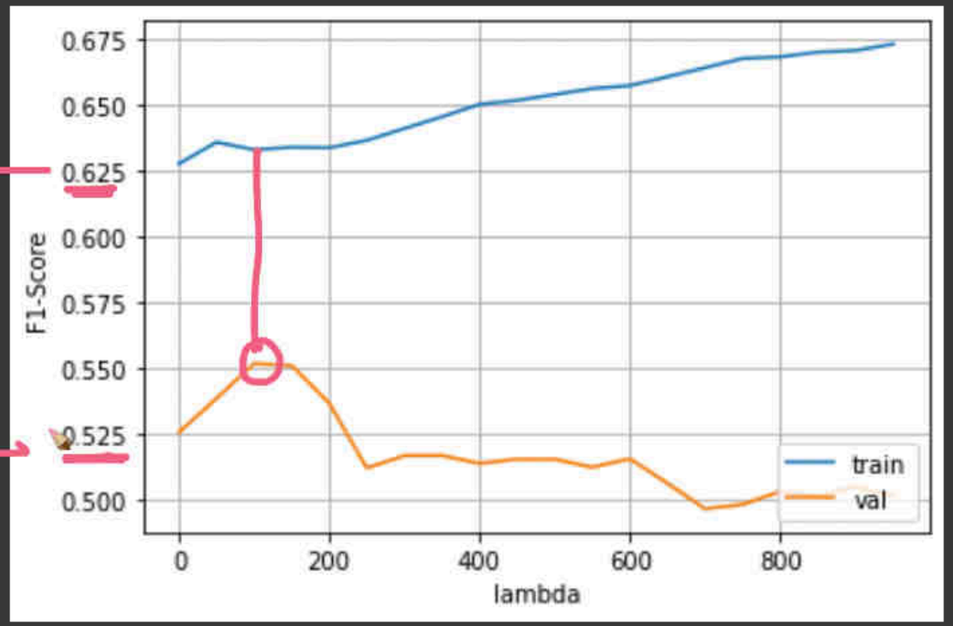
```

```
plt.grid()
plt.show()
```

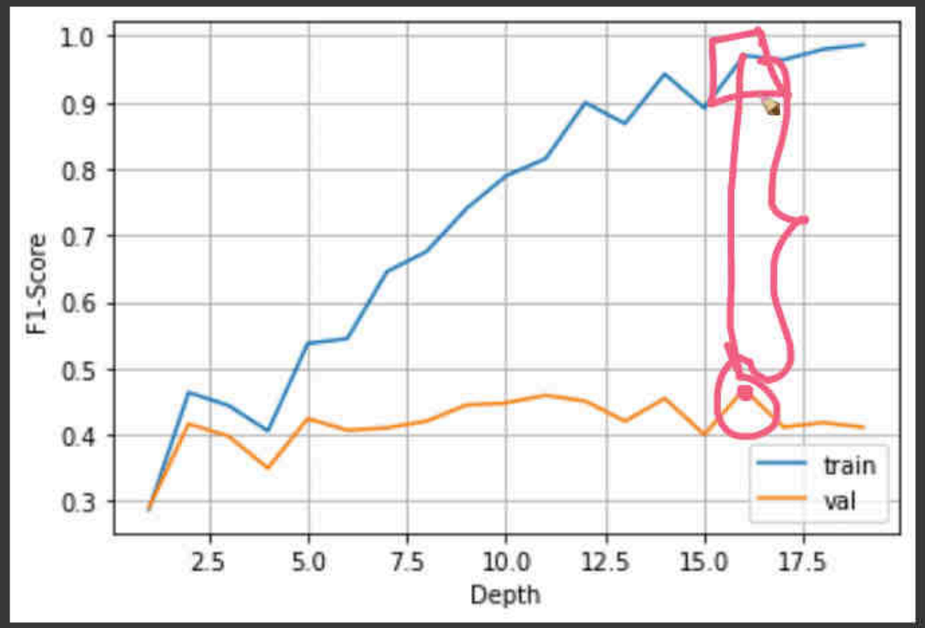


Logistic Reg

```
# minority class needs more weighting

# Hyper-pram tuning
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import make_pipeline
from sklearn.metrics import f1_score
```

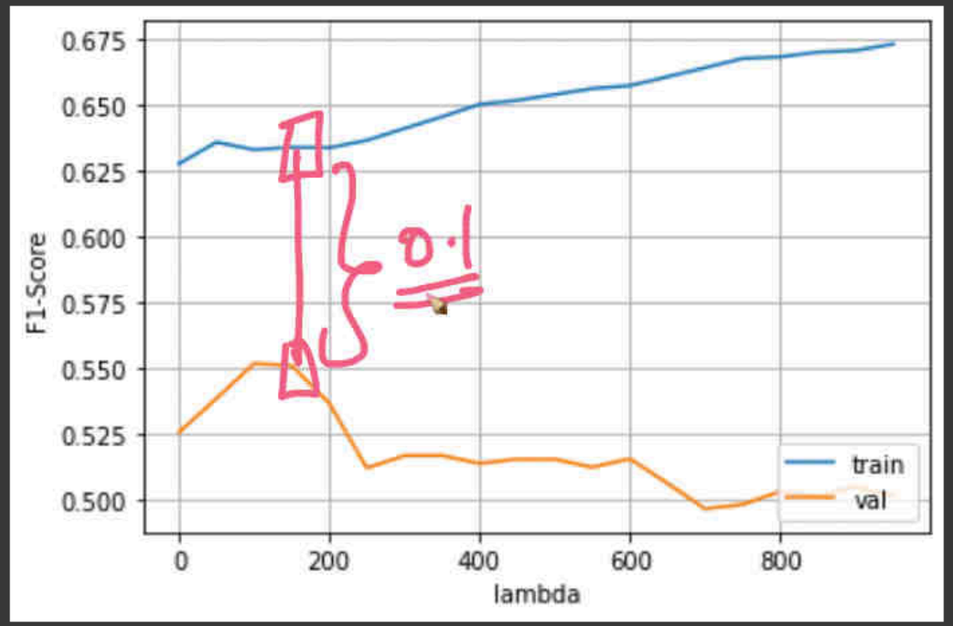
```
plt.plot(list(np.arange(l,u,d)), val_scores, label="val")
plt.legend(loc='lower right')
plt.xlabel("Depth")
plt.ylabel("F1-Score")
plt.grid()
plt.show()
```




```
[210] # Model with depth_best
      from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score, f1_score, precision_re

      best_idx = np.argmax(val_scores)
```

```
[ ]  plt.grid()
     plt.show()
```

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[ ]  # minority class needs more weighting

     # Hyper-pram tuning
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     from sklearn.pipeline import make_pipeline
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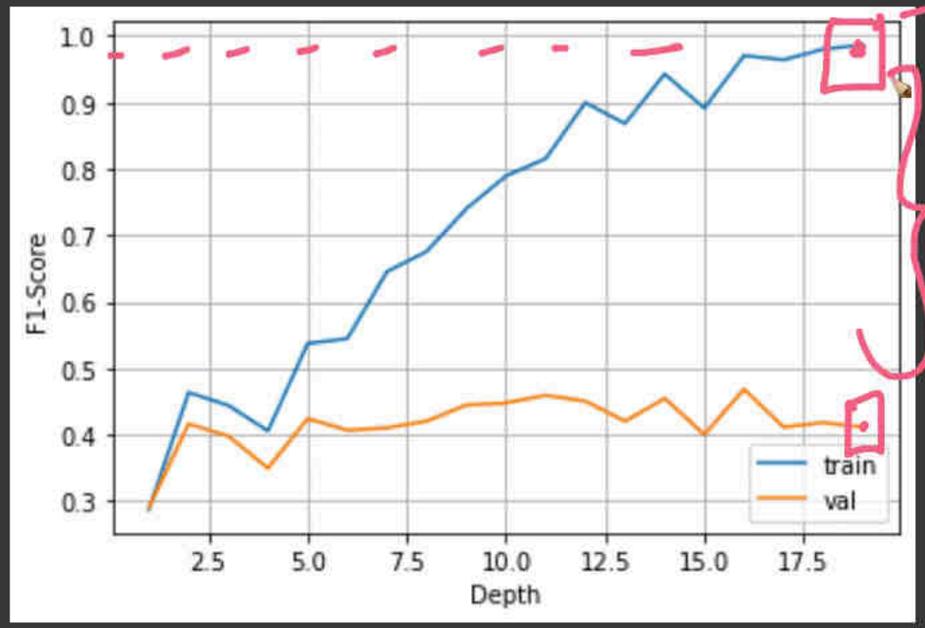
```




```
[210] # Model with depth_best
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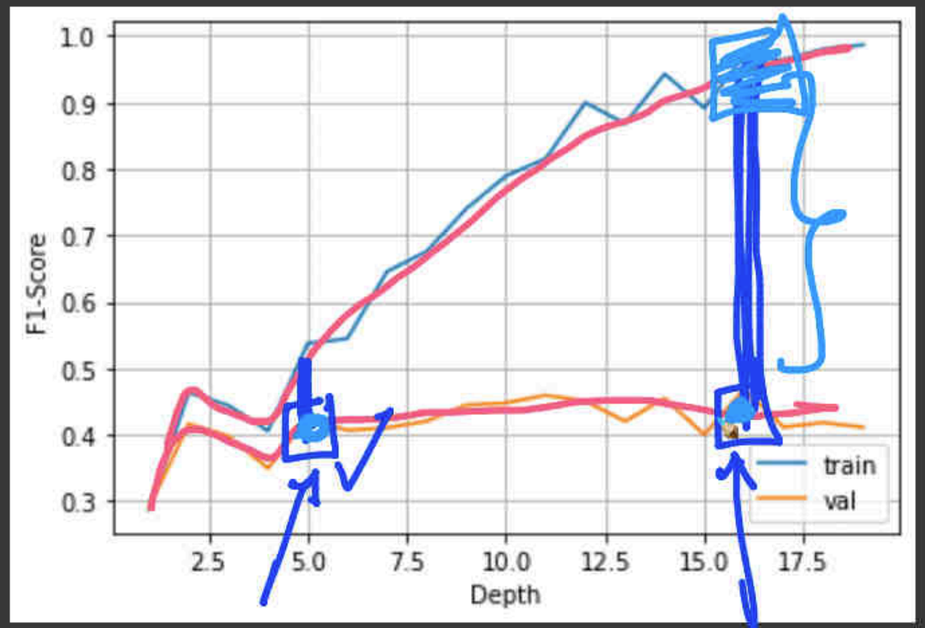

808

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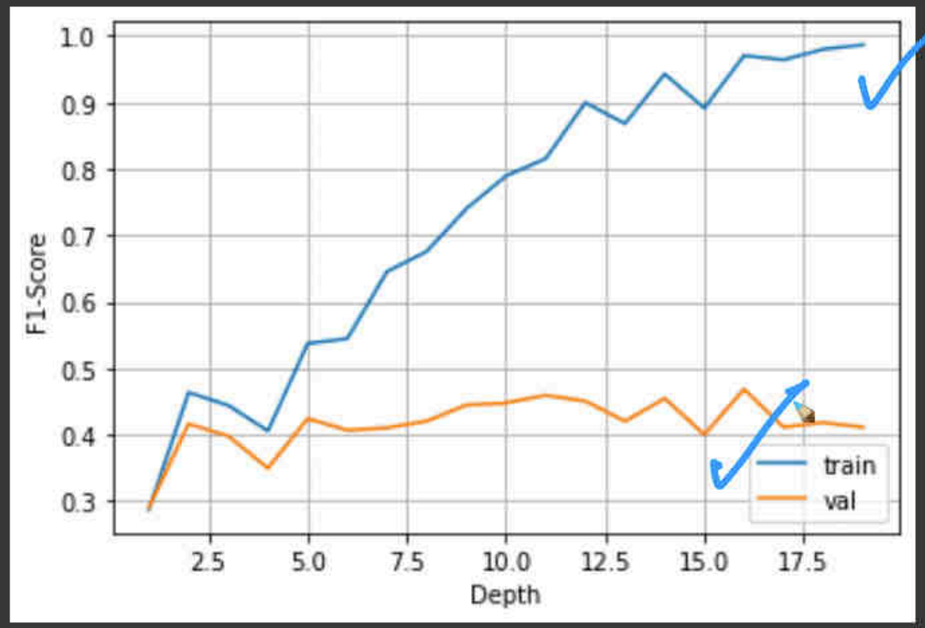
```

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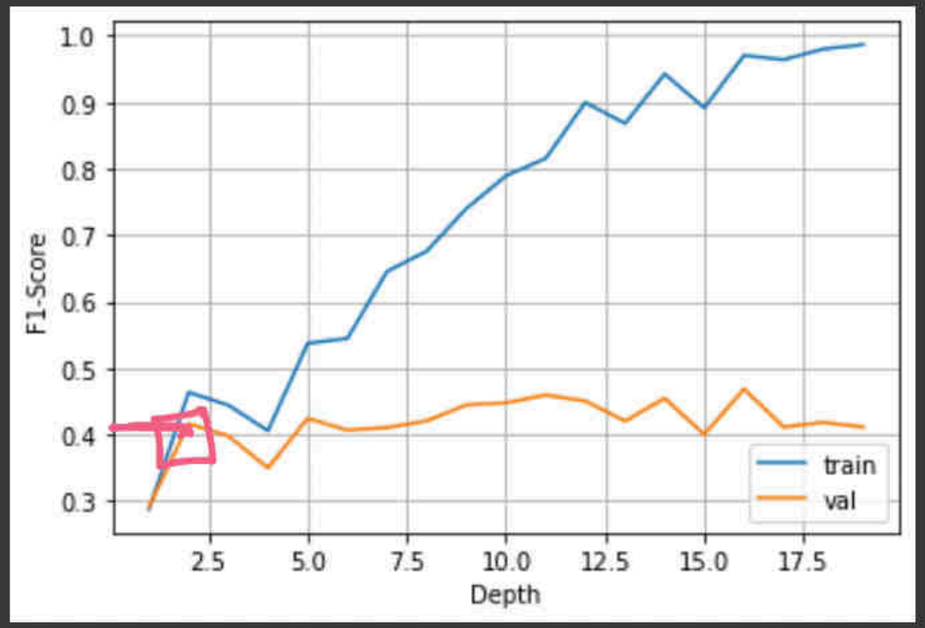
```

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      best_idx = np.argmax(val_scores)
```

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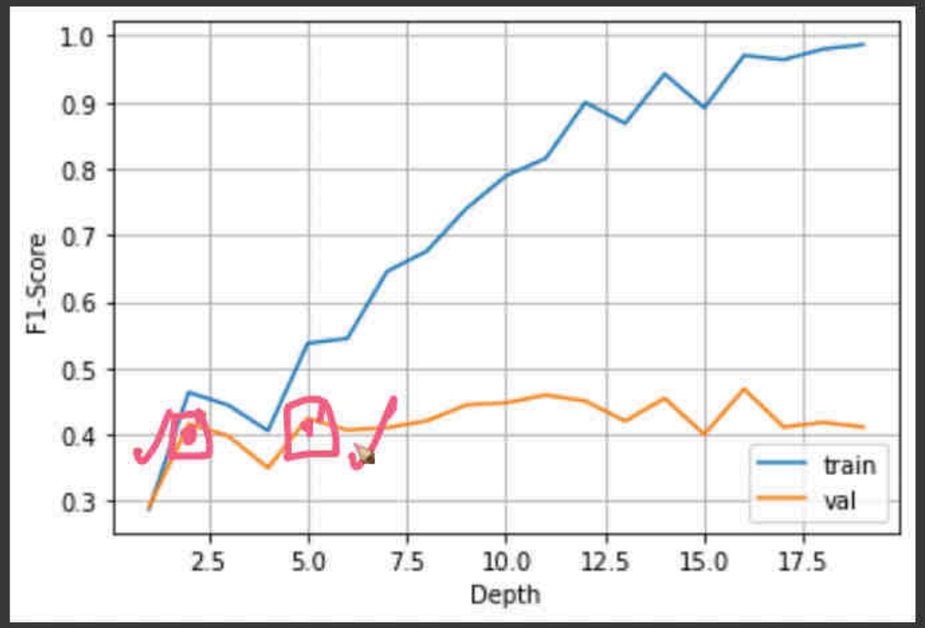
plt.grid()
plt.show()
```



[210]
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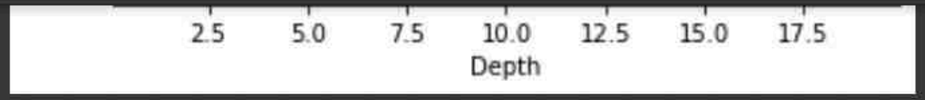
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score, f1_score, precision_re

best_idx = np.argmax(val_scores)
```




```
# Model with depth_best
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score, f1_score, precision_re

best_idx = np.argmax(val_scores)
l_best = 5 #l+d*best_idx
print(l_best)
clf = DecisionTreeClassifier(random_state=0, max_depth=l_best, class_weight={ 0:0.1, 1:w } )
clf.fit(X_train, y_train)

y_pred_val = clf.predict(X_val)
val_score = f1_score(y_val, y_pred_val)

print(val_score)

confusion_matrix(y_val, y_pred_val)
```

```
5
0.42424242424242425
array([[164,  80],
       [ 15,  35]])
```

```
[211] # Feature importance
```

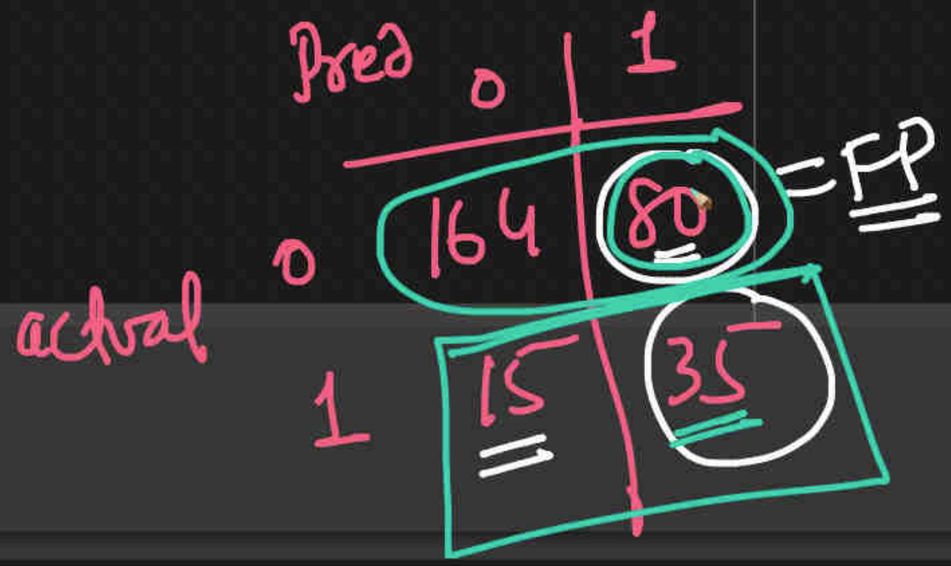
```
best_idx = np.argmax(val_scores)
l_best = 2 #l+d*best_idx
print(l_best)
clf = DecisionTreeClassifier(random_state=0, max_depth=l_best, class_weight={ 0:0.1, 1:w } )
clf.fit(X_train, y_train)

y_pred_val = clf.predict(X_val)
val_score = f1_score(y_val, y_pred_val)

print(val_score)

confusion_matrix(y_val, y_pred_val)
```

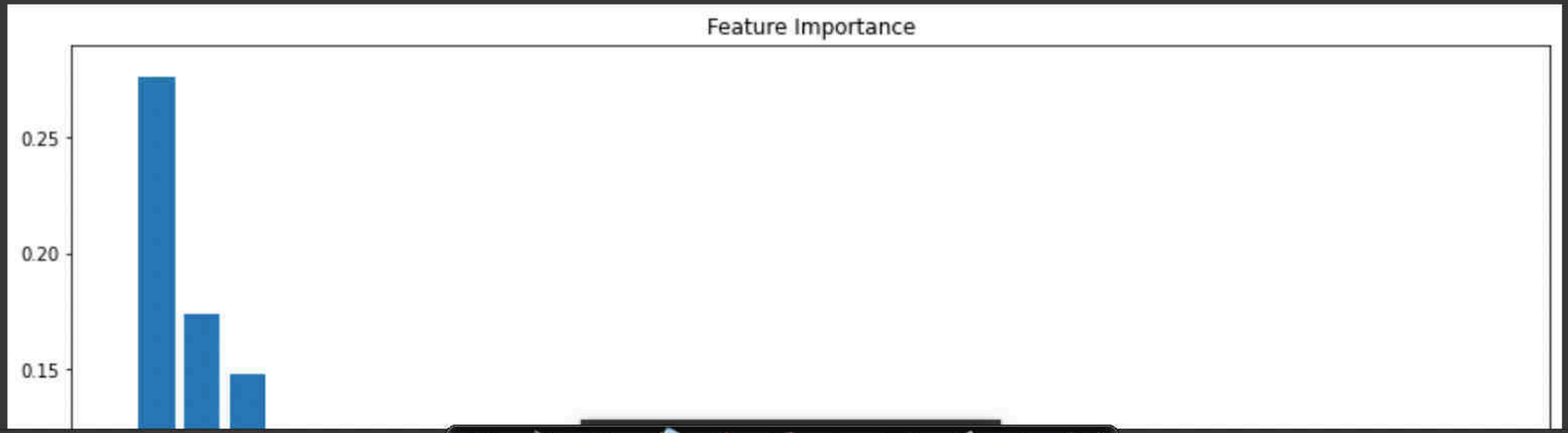
```
2
0.41618497109826585
array([[157,  87],
       [ 14,  36]])
```




```
[211] # Feature importance
      importances = clf.feature_importances_
      indices = np.argsort(importances)[::-1] # Sort feature importances in descending order
      names = [X_train.columns[i] for i in indices] # Rearrange feature names so they match the sorted feature importance
      plt.figure(figsize=(15, 7)) # Create plot
      plt.title("Feature Importance") # Create plot title
```

```
array([[157,  87],
       [ 14,  36]])
```

```python
# Feature importance
importances = clf.feature_importances_
indices = np.argsort(importances)[::-1] # Sort feature importances in descending order
names = [X_train.columns[i] for i in indices] # Rearrange feature names so they match the sorted feature importance
plt.figure(figsize=(15, 7)) # Create plot
plt.title("Feature Importance") # Create plot title
plt.bar(range(X_train.shape[1]), importances[indices]) # Add bars
plt.xticks(range(X_train.shape[1]), names, rotation=90) # Add feature names as x-axis labels
plt.show() # Show plot
```



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sklearn.tree.DecisionTreeClassifier
Examples using sklearn.tree.DecisionTreeClassifier

ccp_alpha : *non-negative float, default=0.0*

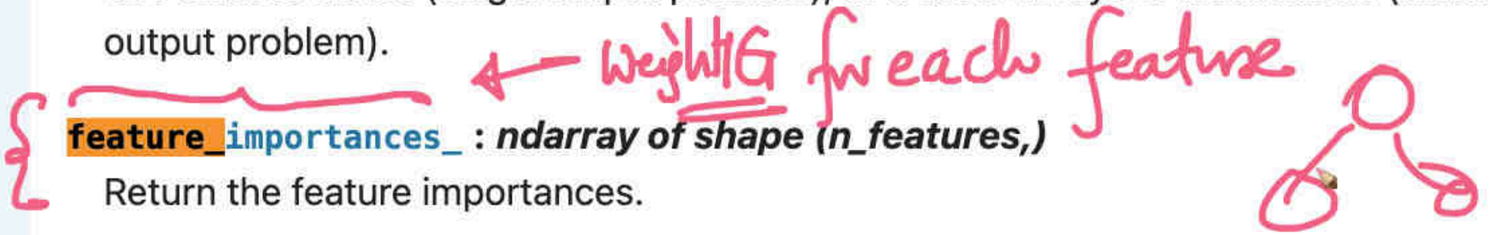
Complexity parameter used for Minimal Cost-Complexity Pruning. The subtree with the largest cost complexity that is smaller than `ccp_alpha` will be chosen. By default, no pruning is performed. See Minimal Cost-Complexity Pruning for details.

New in version 0.22.

Attributes:

classes_ : *ndarray of shape (n_classes,) or list of ndarray*

The classes labels (single output problem), or a list of arrays of class labels (multi-output problem).



feature_importances_ : *ndarray of shape (n_features,)*

Return the feature importances.

max_features_ : *int*

The inferred value of max_features.

n_classes_ : *int or list of int*

The number of classes (for single output problems), or a list containing the number of classes for each output (for multi-output problems).

n_features_ : *int*

DEPRECATED: The attribute `n_features_` is deprecated in 1.0 and will be removed in

```
array([[157,  87],
       [ 14,  36]])
```

```python
# Feature importance
importances = clf.feature_importances_
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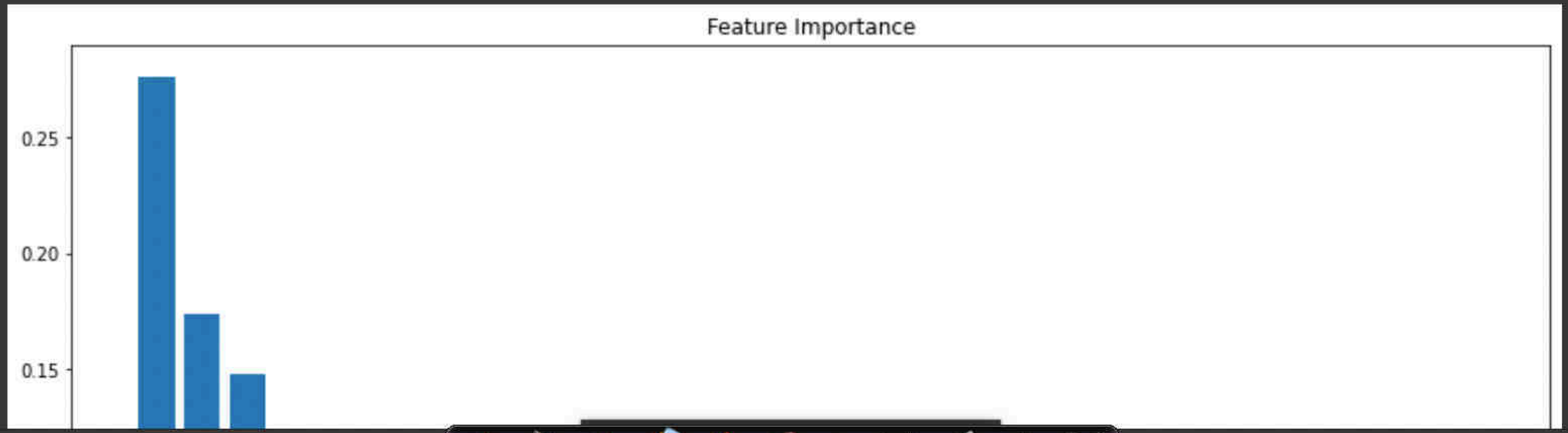

```
array([[157,  87],
       [ 14,  36]])
```

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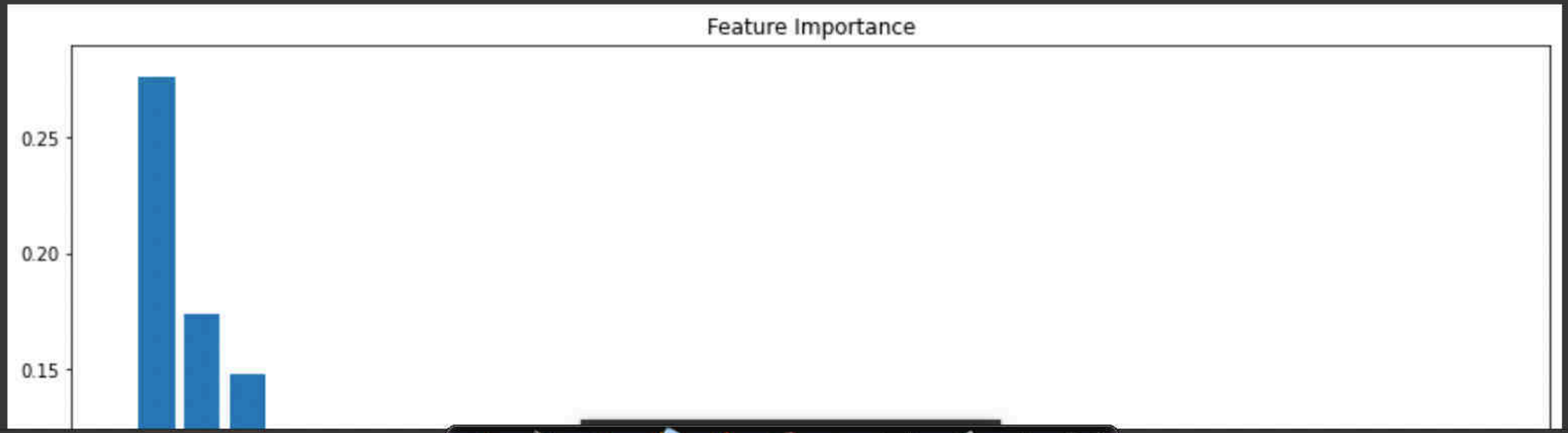

```
array([[157,  87],
       [ 14,  36]])
```

f1 f2 ... fd

0.26 0.24 ...

```
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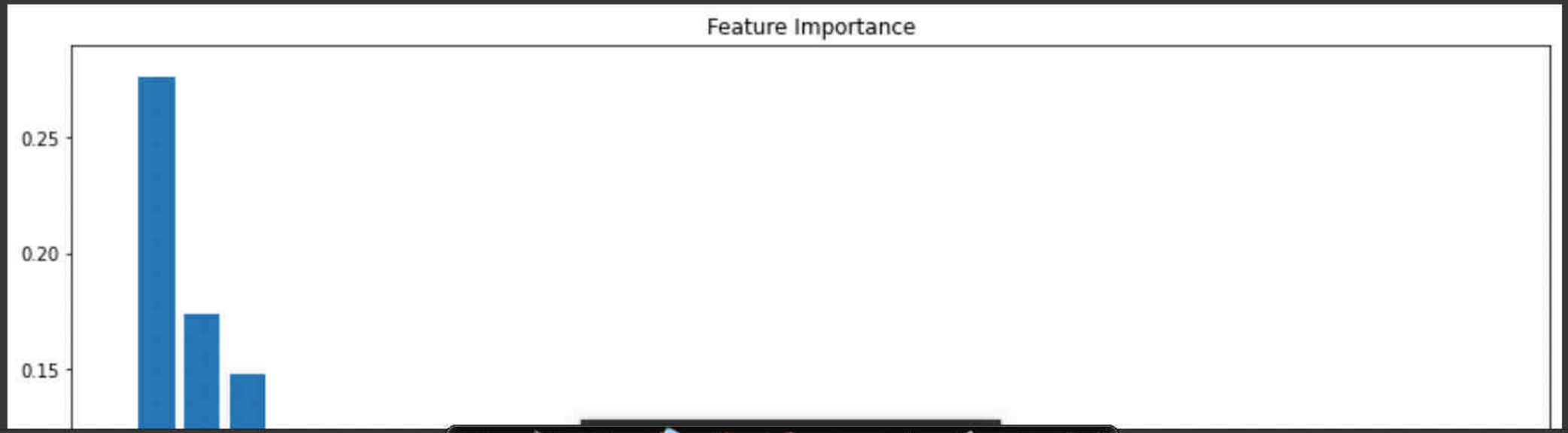

```
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```

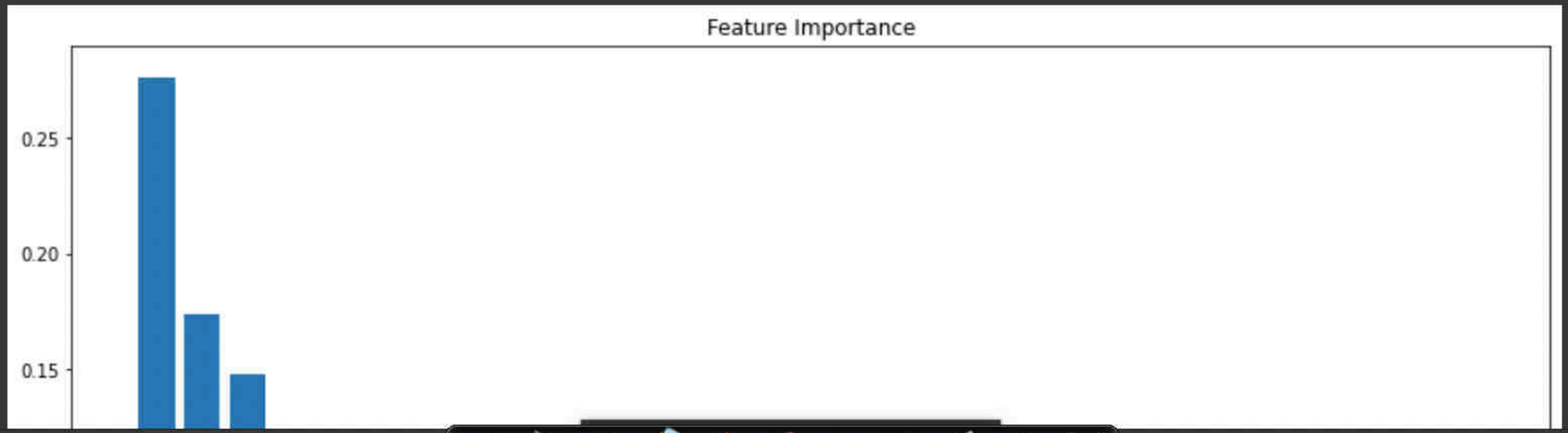

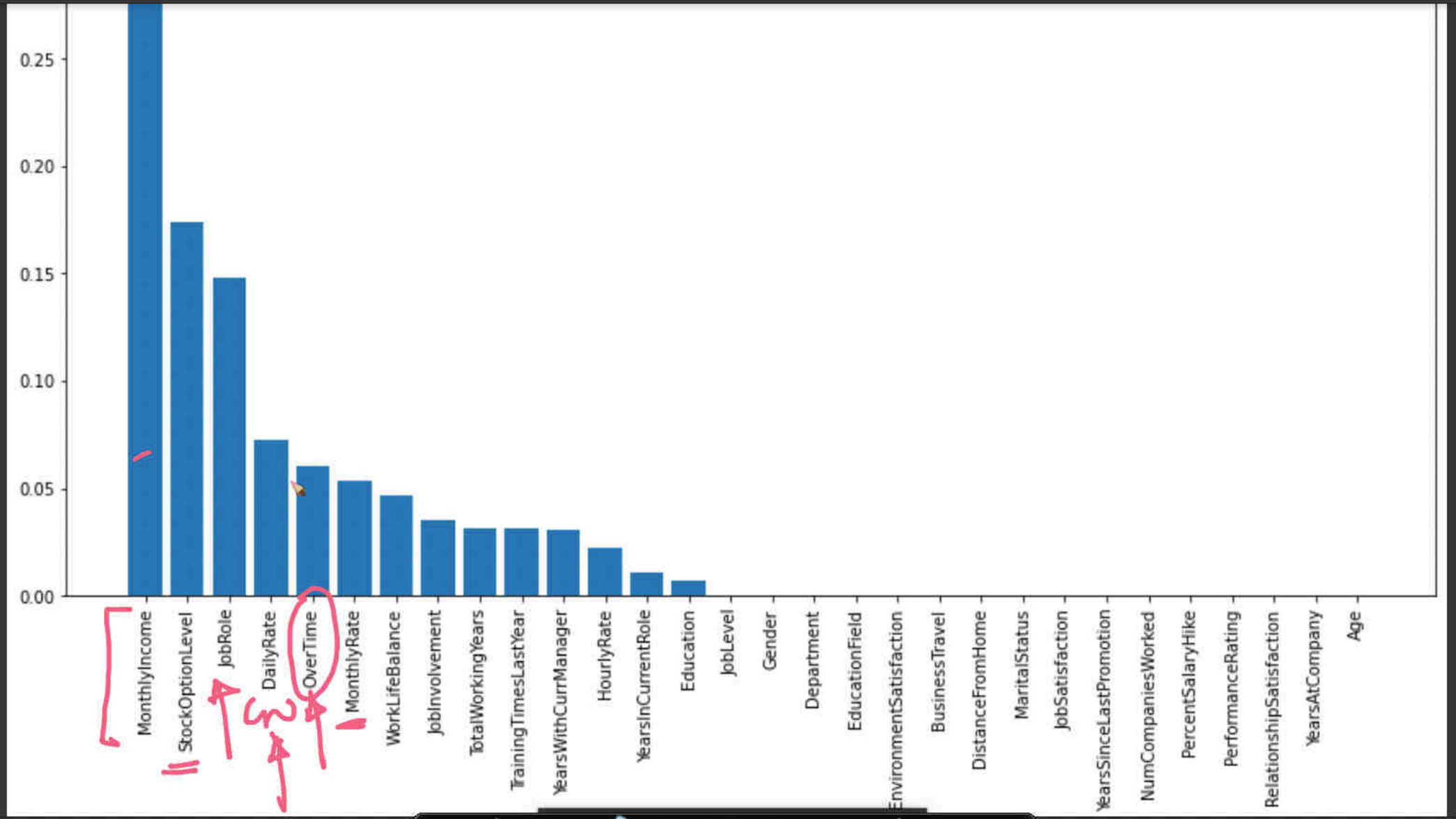

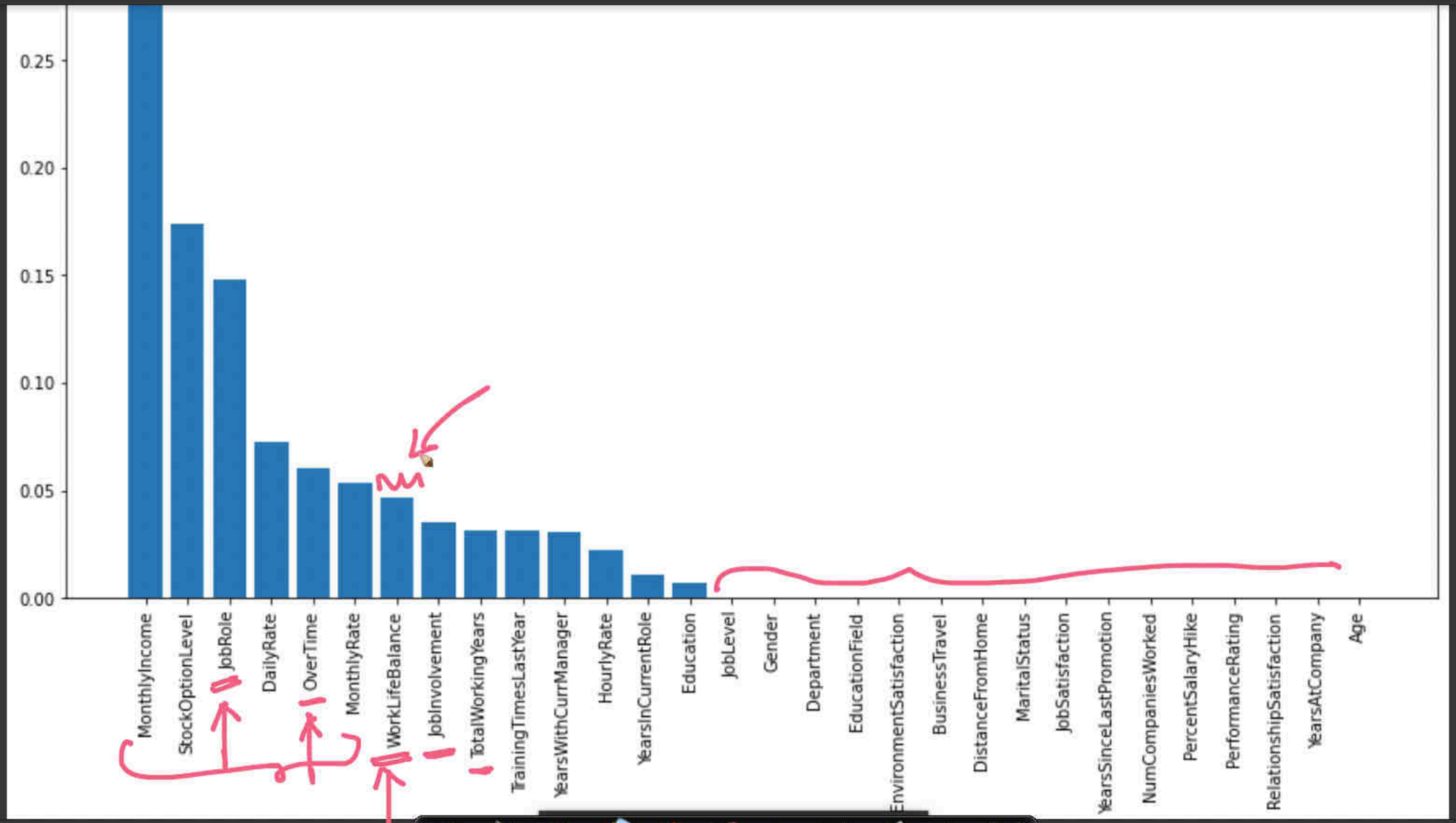
0.25
0.20
0.15
0.10
0.05
0.00
MonthlyIncome
StockOptionLevel
JobRole
DailyRate
OverTime
MonthlyRate
WorkLifeBalance
JobInvolvement
TotalWorkingYears
TrainingTimesLastYear
YearsWithCurrManager
HourlyRate
YearsInCurrentRole
Education
JobLevel
Gender
Department
EducationField
EnvironmentSatisfaction
BusinessTravel
DistanceFromHome
MaritalStatus
JobSatisfaction
YearsSinceLastPromotion
NumCompaniesWorked
PercentSalaryHike
PerformanceRating
RelationshipSatisfaction
YearsAtCompany
Age

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DT and RF.ipynb - Colaborator | sklearn.tree.DecisionTreeClass | sklearn.ensemble.RandomFore | sklearn.preprocessing.LabelEr | Target Encoder — Category En | Imbalanced Data.ipynb - Colab

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RAM Disk

[216]
```
train_scores = []
val_scores = []

l=1
u=20
d=1
w=3.0
num_learners=100
row_sampling_rate = 0.75

for depth in np.arange(l,u,d):
  clf = RandomForestClassifier(max_depth=depth, max_samples=row_sampling_rate, n_estimators=num_learners, random_st
  clf.fit(X_train, y_train)
  train_y_pred = clf.predict(X_train)
  val_y_pred = clf.predict(X_val)
  train_score = f1_score(y_train, train_y_pred)
  val_score = f1_score(y_val, val_y_pred)
  train_scores.append(train_score)
  val_scores.append(val_score)
```

M1

0.1 3.0

0.1 1.0

[217]
```
import matplotlib.pyplot as plt

plt.figure()
```

80 / 82

```
[216] train_scores = []
      val_scores = []

      l=1
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      d=1
      w=3.0
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        train_y_pred = clf.predict(X_train)
        val_y_pred = clf.predict(X_val)
        train_score = f1_score(y_train, train_y_pred)
        val_score = f1_score(y_val, val_y_pred)
        train_scores.append(train_score)
        val_scores.append(val_score)
```

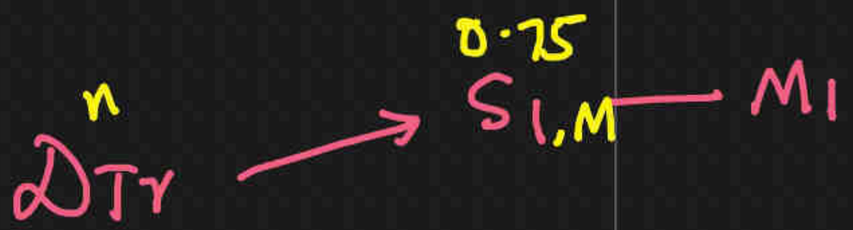


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[217] import matplotlib.pyplot as plt

      plt.figure()
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[216] train_scores = []
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        train_y_pred = clf.predict(X_train)
        val_y_pred = clf.predict(X_val)
        train_score = f1_score(y_train, train_y_pred)
        val_score = f1_score(y_val, val_y_pred)
        train_scores.append(train_score)
        val_scores.append(val_score)
```

Xg boost

```
[217] import matplotlib.pyplot as plt

      plt.figure()
```

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DT and RF.ipynb - Colaborator | sklearn.tree.DecisionTreeClass | sklearn.ensemble.RandomFore | sklearn.preprocessing.LabelEn | Target Encoder — Category En | Imbalanced Data.ipynb - Colab

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Update

+ Code + Text

RAM Disk

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      val_scores = []

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      u=20
      d=1
      w=3.0
      num_learners=100
      row_sampling_rate = 0.75


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        train_y_pred = clf.predict(X_train)
        val_y_pred = clf.predict(X_val)
        train_score = f1_score(y_train, train_y_pred)
        val_score = f1_score(y_val, val_y_pred)
        train_scores.append(train_score)
        val_scores.append(val_score)
```

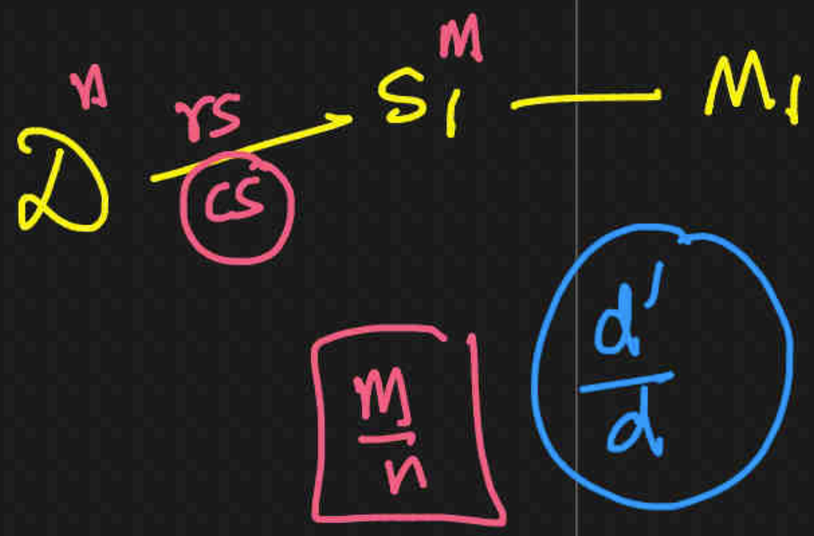


```
[217] import matplotlib.pyplot as plt

      plt.figure()
```

83 / 85

```
train_scores = []
val_scores = []

l=1
u=20
d=1
w=3.0
num_learners=100
row_sampling_rate = 0.75


for depth in np.arange(l,u,d):
  clf = RandomForestClassifier(max_depth=depth, max_samples=row_sampling_rate, n_estimators=num_learners, random_st
  clf.fit(X_train, y_train)
  train_y_pred = clf.predict(X_train)
  val_y_pred = clf.predict(X_val)
  train_score = f1_score(y_train, train_y_pred)
  val_score = f1_score(y_val, val_y_pred)
  train_scores.append(train_score)
  val_scores.append(val_score)
```

```
[217] import matplotlib.pyplot as plt

      plt.figure()
```

```
train_scores = []
val_scores = []

l=1
u=20
d=1
w=3.0
num_learners=100
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for depth in np.arange(l,u,d):
  clf = RandomForestClassifier(max_depth=depth, max_samples=row_sampling_rate, n_estimators=num_learners, random_st
  clf.fit(X_train, y_train)
  train_y_pred = clf.predict(X_train)
  val_y_pred = clf.predict(X_val)
  train_score = f1_score(y_train, train_y_pred)
  val_score = f1_score(y_val, val_y_pred)
  train_scores.append(train_score)
  val_scores.append(val_score)
```
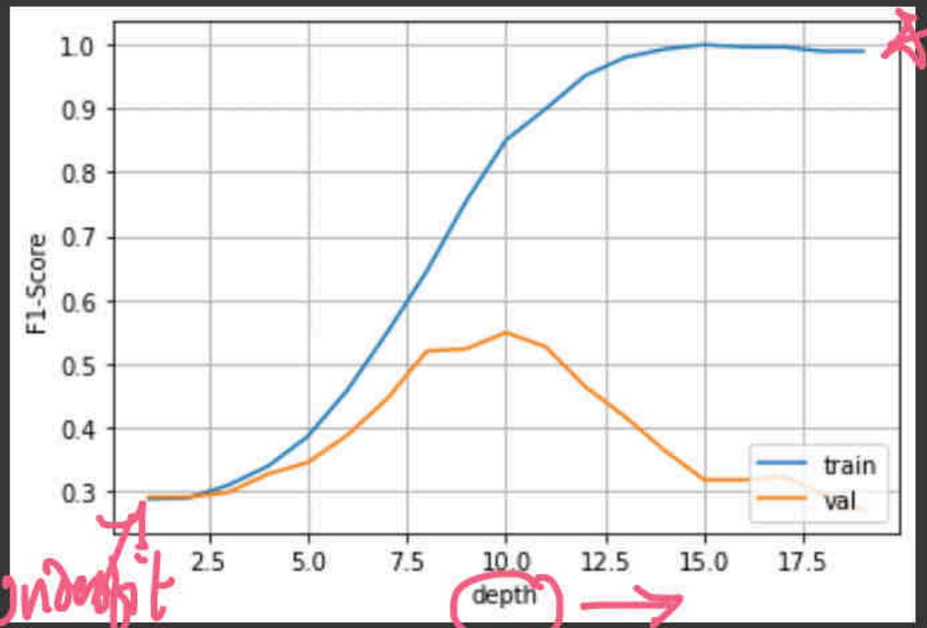

```
[217] import matplotlib.pyplot as plt

      plt.figure()
```

```
plt.figure()
plt.plot(list(np.arange(l,u,d)), train_scores, label="train")
plt.plot(list(np.arange(l,u,d)), val_scores, label="val")
plt.legend(loc='lower right')
plt.xlabel("depth")
plt.ylabel("F1-Score")
plt.grid()
plt.show()
```



overfit

Underfit

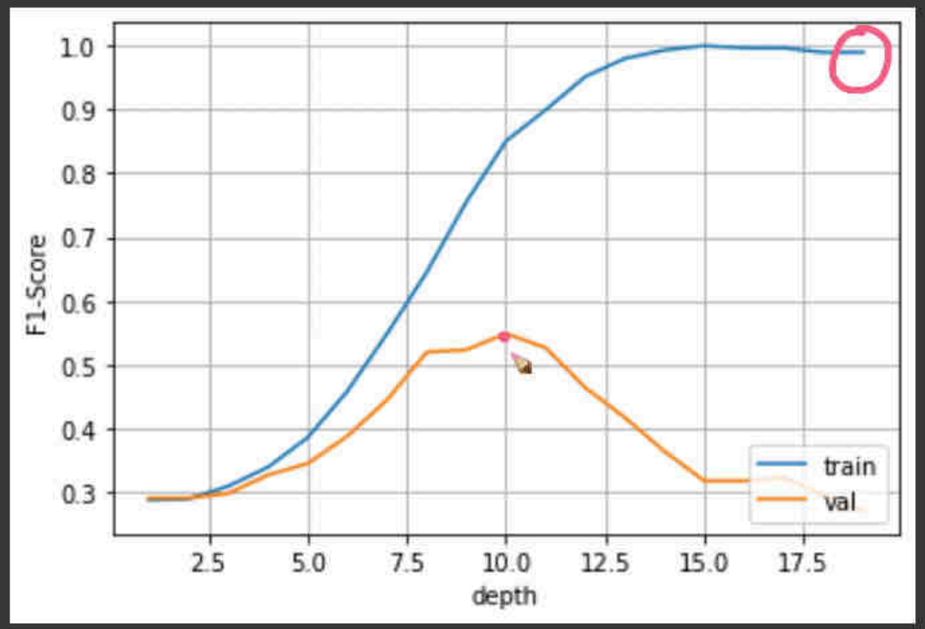
depth ↑

m/n ↓

#base learners ↑

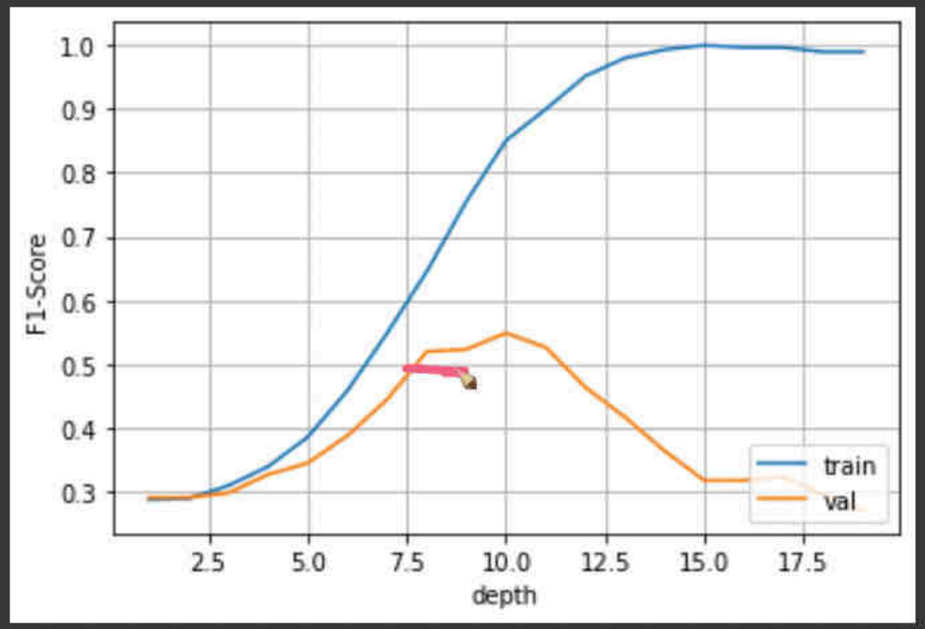
```
[218] # Model with depth best
```

```
plt.figure()
plt.plot(list(np.arange(1,u,d)), train_scores, label="train")
plt.plot(list(np.arange(1,u,d)), val_scores, label="val")
plt.legend(loc='lower right')
plt.xlabel("depth")
plt.ylabel("F1-Score")
plt.grid()
plt.show()
```



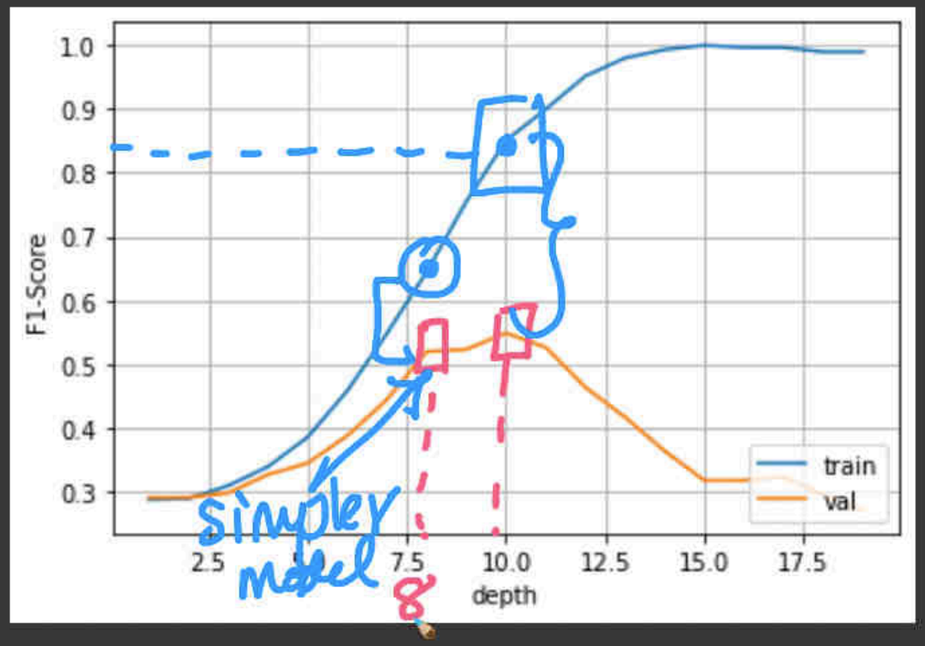

```
[218] # Model with depth best
```

```
[242] plt.plot(list(np.arange(1,u,d)), train_scores, label="train")
      plt.plot(list(np.arange(1,u,d)), val_scores, label="val")
      plt.legend(loc='lower right')
      plt.xlabel("depth")
      plt.ylabel("F1-Score")
      plt.grid()
      plt.show()
```



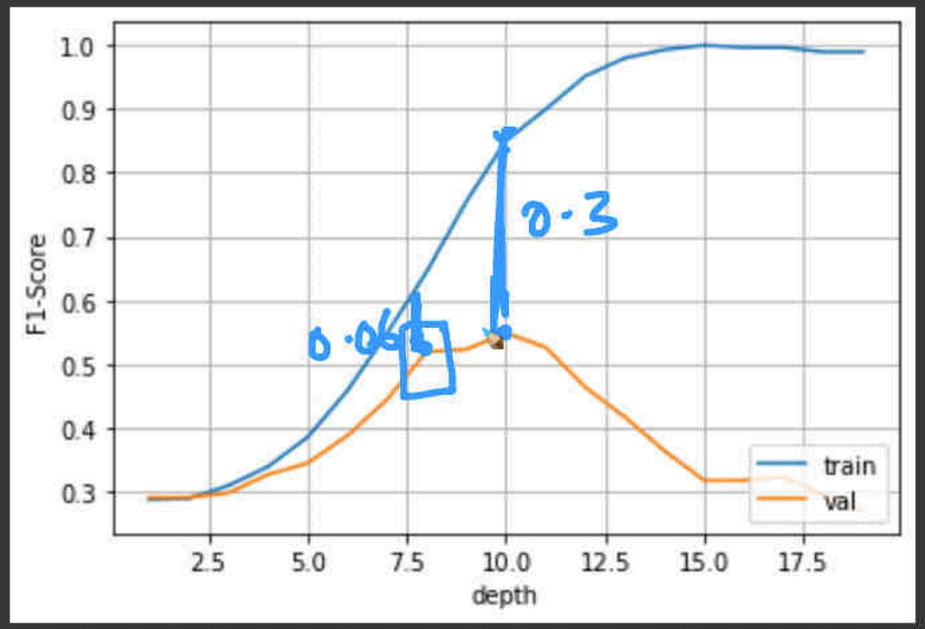

```
[218] # Model with depth_best
      from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score, f1_score, precision_re
```

```
[242] plt.plot(list(np.arange(1,u,d)), val_scores, label="val")
      plt.legend(loc='lower right')
      plt.xlabel("depth")
      plt.ylabel("F1-Score")
      plt.grid()
      plt.show()
```




```
[218] # Model with depth_best
      from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score, f1_score, precision_re
```

```
[242] plt.plot(list(np.arange(1,u,d)), val_scores, label="val")
      plt.legend(loc='lower right')
      plt.xlabel("depth")
      plt.ylabel("F1-Score")
      plt.grid()
      plt.show()
```




```
[218] # Model with depth_best
      from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score, f1_score, precision_re
```

depth

```
# Model with depth_best
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score, f1_score, precision_re

best_idx = np.argmax(val_scores)
l_best = 8 #l+d*best_idx
clf = RandomForestClassifier(max_depth=l_best, max_samples = row_sampling_rate, n_estimators=num_learners, random_s
clf.fit(X_train, y_train)

y_pred_val = clf.predict(X_val)
val_score = f1_score(y_val, y_pred_val)

print(val_score)

confusion_matrix(y_val, y_pred_val)
```

```
0.5194805194805195
array([[180,  64],
       [ 10,  40]])
```

```
[219] # Feature importance
      importances = clf.feature_importances_
      indices = np.argsort(importances)[::-1] # Sort feature importances in descending order
      names = [X_train.columns[i] for i in indices] # Rearrange feature names so they match the sorted feature importance
```

Chrome File Edit View History Bookmarks Profiles Tab Window Help 10:26

DT and RF.ipynb - Colaborator | sklearn.tree.DecisionTreeClass | sklearn.ensemble.RandomFore | sklearn.preprocessing.LabelEr | Target Encoder — Category En | Imbalanced Data.ipynb - Colab

colab.research.google.com/drive/1d2HJ9AKulf83i7pwmDrL-2FOCncFubRF#scrollTo=QX-DZt3bsmqh

Update

+ Code + Text

RAM Disk

[239]
0s

```
print(val_score)

confusion_matrix(y_val, y_pred_val)
```

```
2
0.41618497109826585
array([[157,  87],
       [ 14,  36]])
```

[211]
0s

```
# Feature importance
importances = clf.feature_importances_
indices = np.argsort(importances)[::-1] # Sort feature importances in descending order
names = [X_train.columns[i] for i in indices] # Rearrange feature names so they match the sorted feature importance
plt.figure(figsize=(15, 7)) # Create plot
plt.title("Feature Importance") # Create plot title
plt.bar(range(X_train.shape[1]), importances[indices]) # Add bars
plt.xticks(range(X_train.shape[1]), names, rotation=90) # Add feature names as x-axis labels
plt.show() # Show plot
```

92 / 94

```
clf = RandomForestClassifier(max_depth=l_best, max_samples = row_sampling_rate, n_estimat
clf.fit(X_train, y_train)

y_pred_val = clf.predict(X_val)
val_score = f1_score(y_val, y_pred_val)

print(val_score)

confusion_matrix(y_val, y_pred_val)
```

```
0.5194805194805195
array([[180,  64],
       [ 10,  40]])
```

```
[219] # Feature importance
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plt.xticks(range(X_train.shape[1]), names, rotation=90) # Add feature names as x-axis labels
plt.show() # Show plot
```

Chrome File Edit View History Bookmarks Profiles Tab Window Help 10:27

DT and RF.ipynb - Colaborator | sklearn.tree.DecisionTreeClass | sklearn.ensemble.RandomFore | sklearn.preprocessing.LabelEr | Target Encoder — Category En | Imbalanced Data.ipynb - Colab

colab.research.google.com/drive/1d2HJ9AKulf83i7pwmDrL-2FOCncFubRF#scrollTo=QX-DZt3bsmqh

Update

+ Code + Text

RAM Disk

[239]
0s

```
y_pred_val = clf.predict(X_val)
val_score = f1_score(y_val, y_pred_val)

print(val_score)

confusion_matrix(y_val, y_pred_val)
```

```
2
0.41618497109826585
array([[157,  87],
       [ 14,  36]])
```

DT: 87, 14

RF: 64, 10

[211]
0s

```
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plt.xticks(range(X_train.shape[1]), names, rotation=90) # Add feature names as x-axis labels
plt.show() # Show plot
```
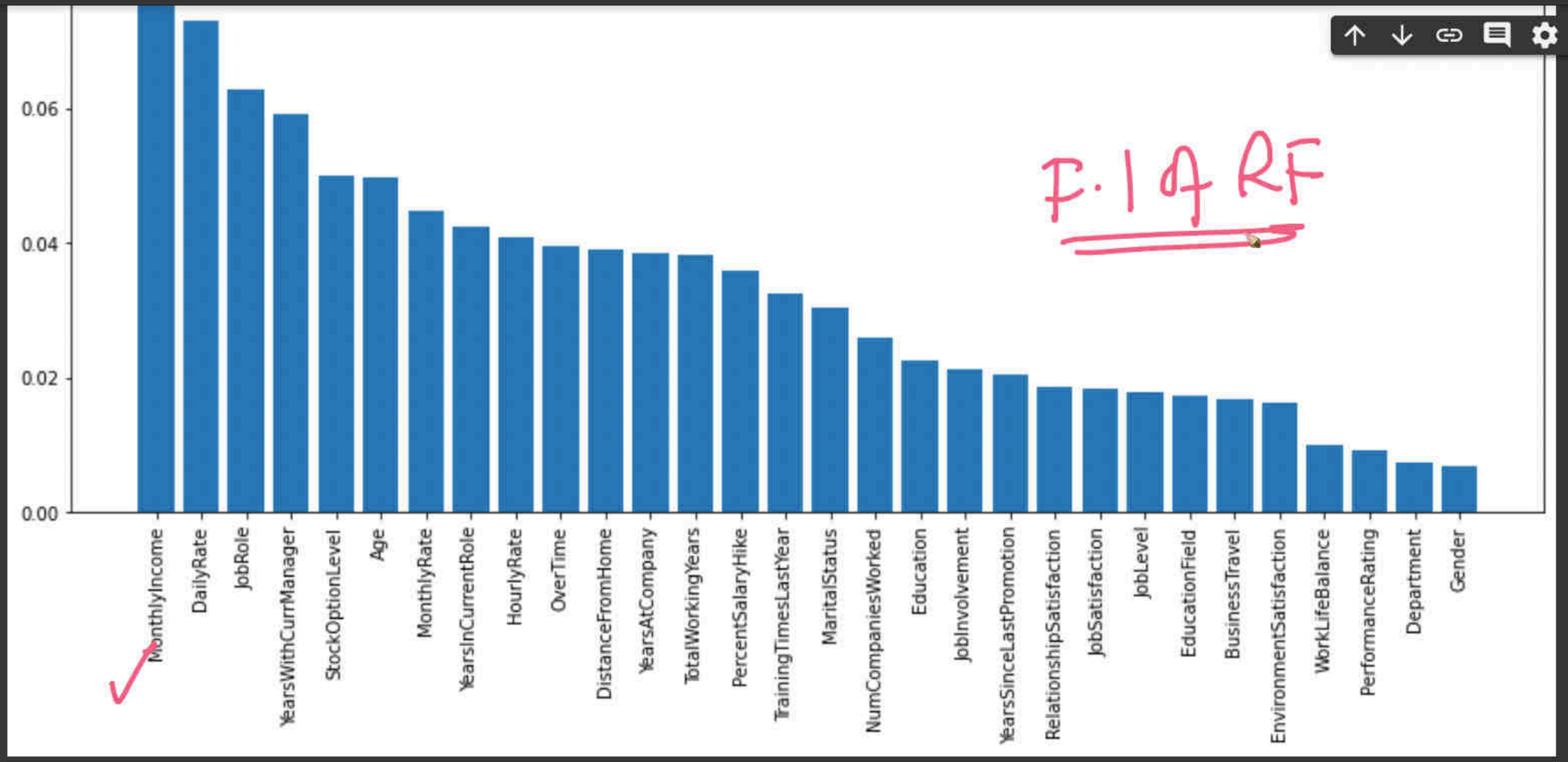
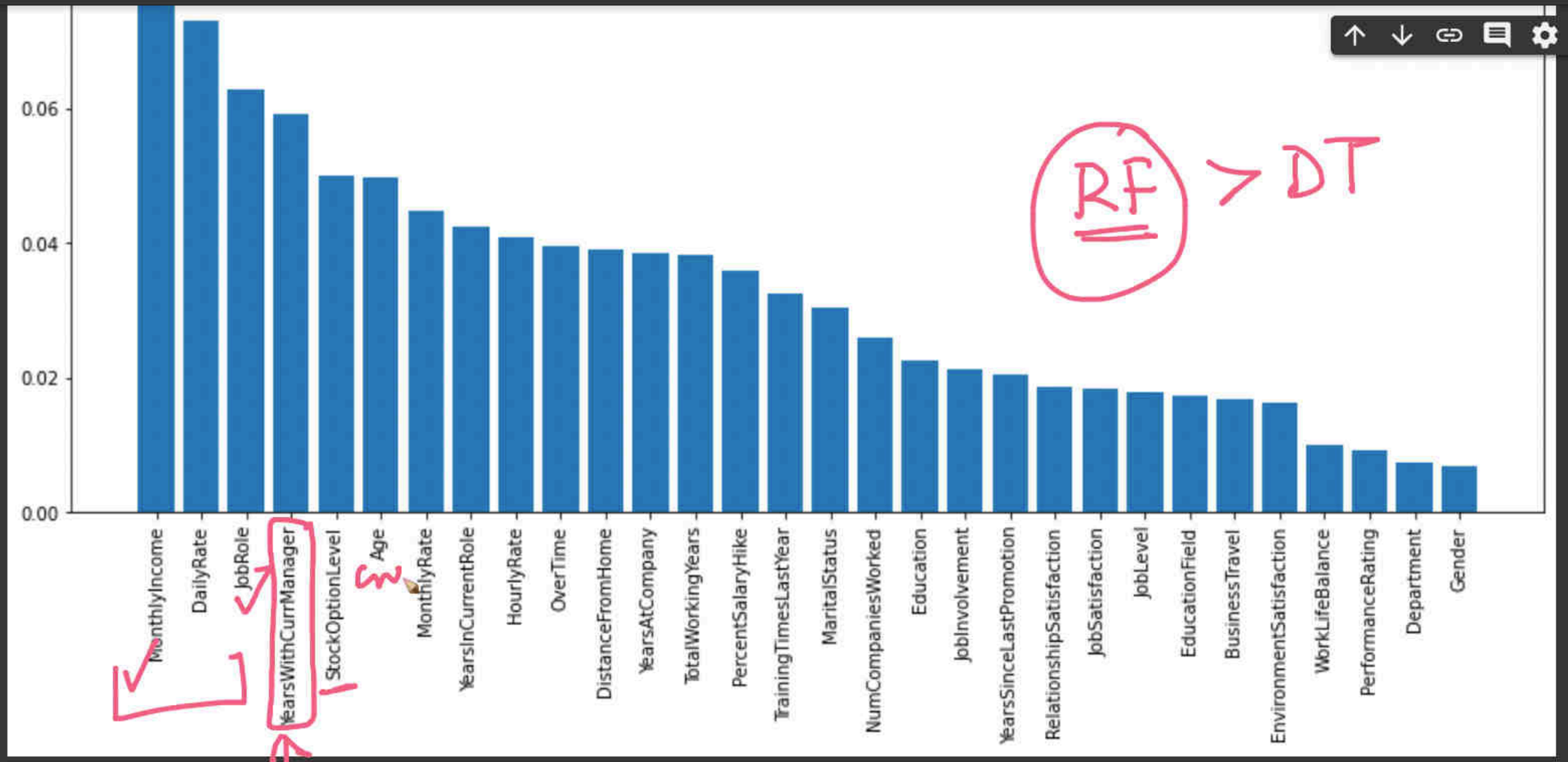

94 / 96



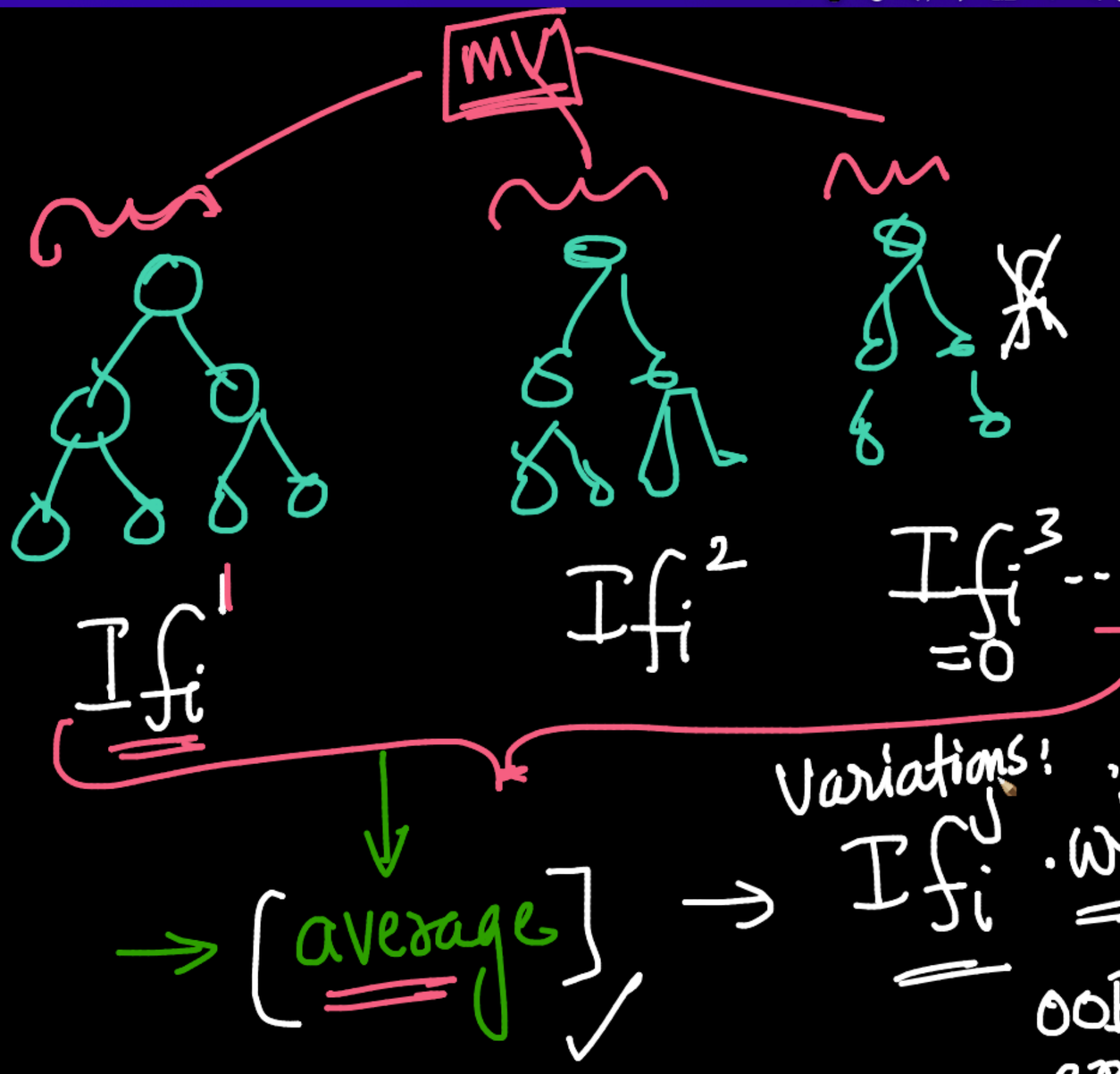
Other Concepts (covered after boosting)

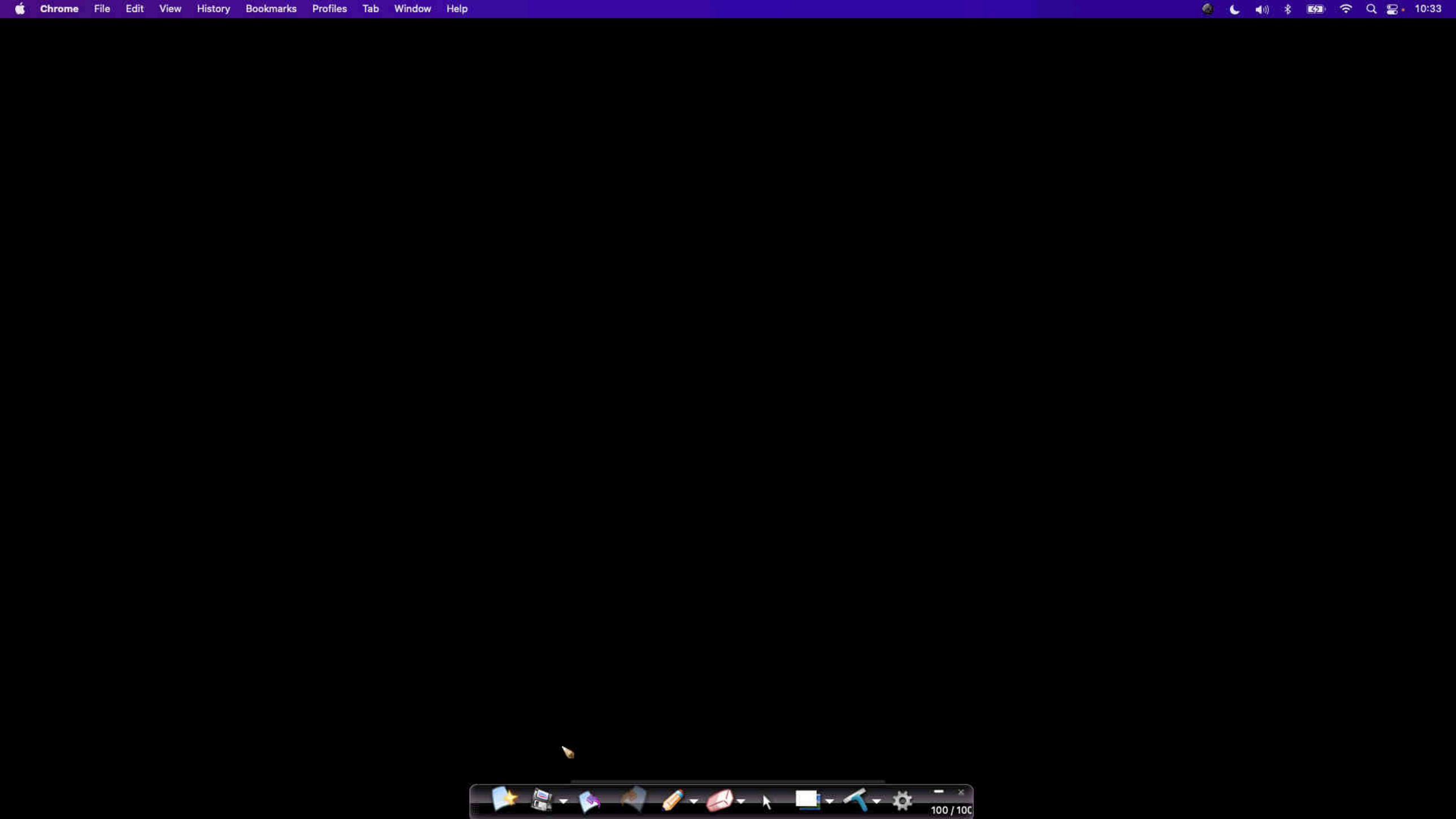


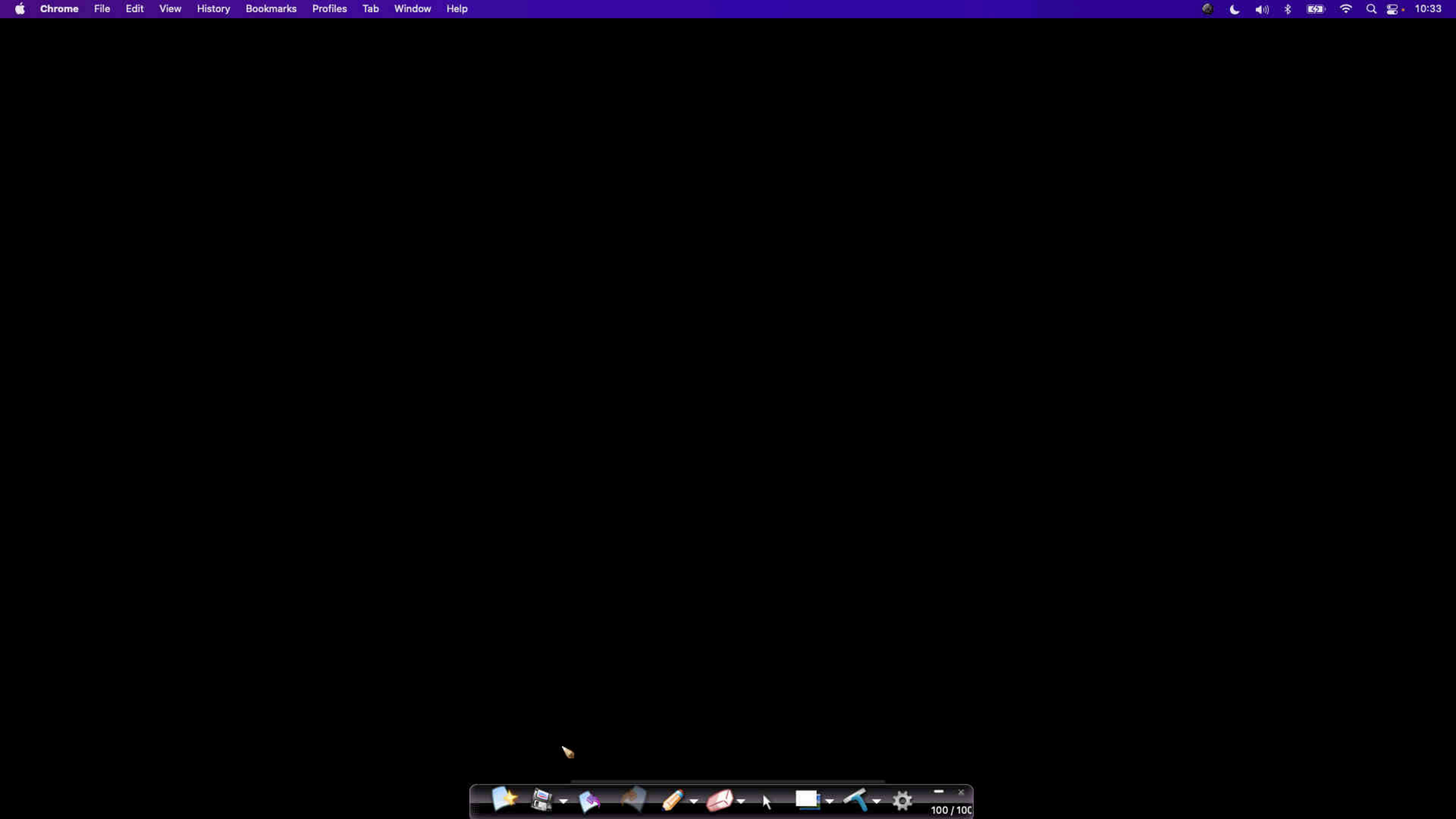
Other Concepts (covered after boosting)

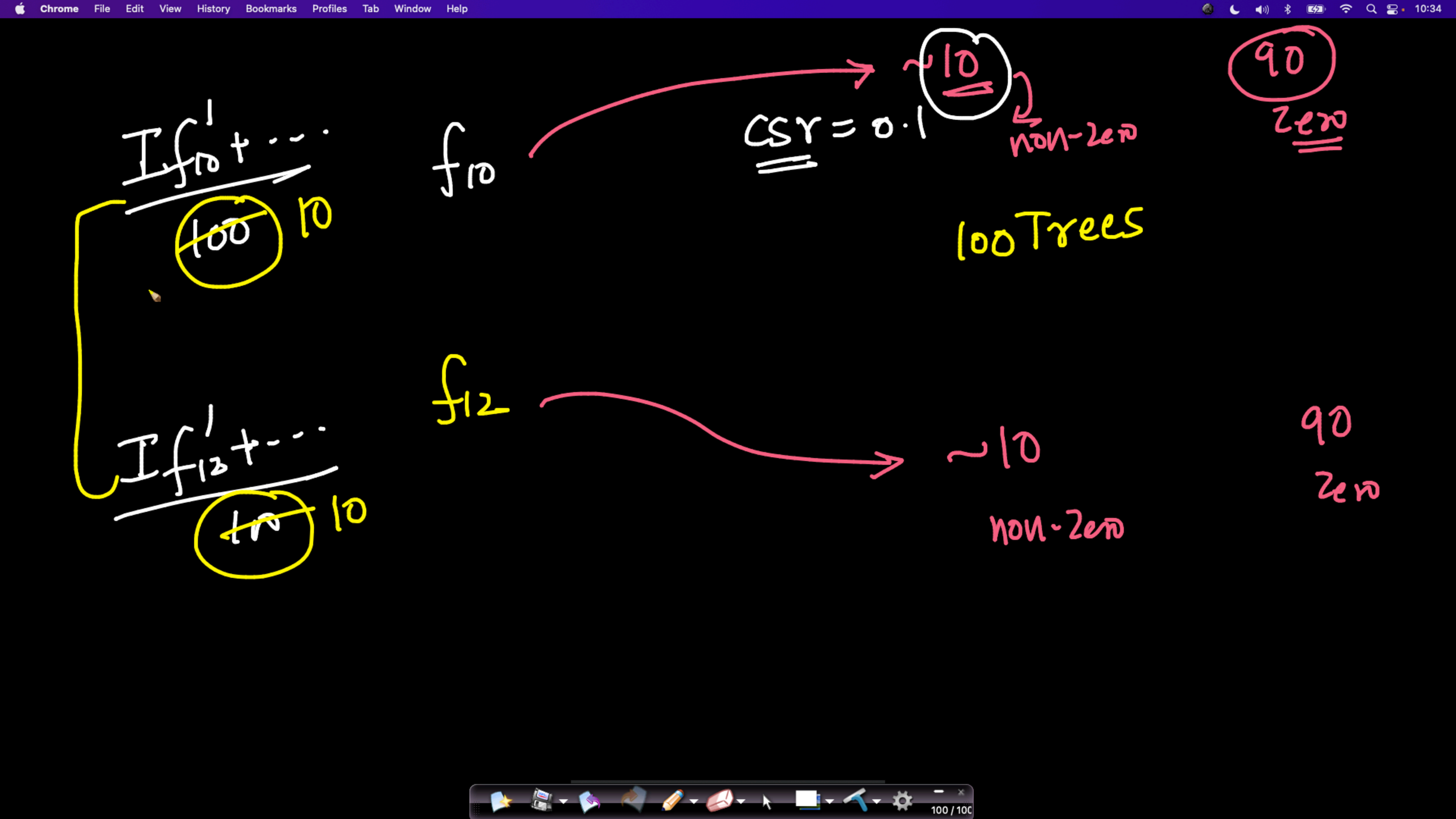
F·I in RF

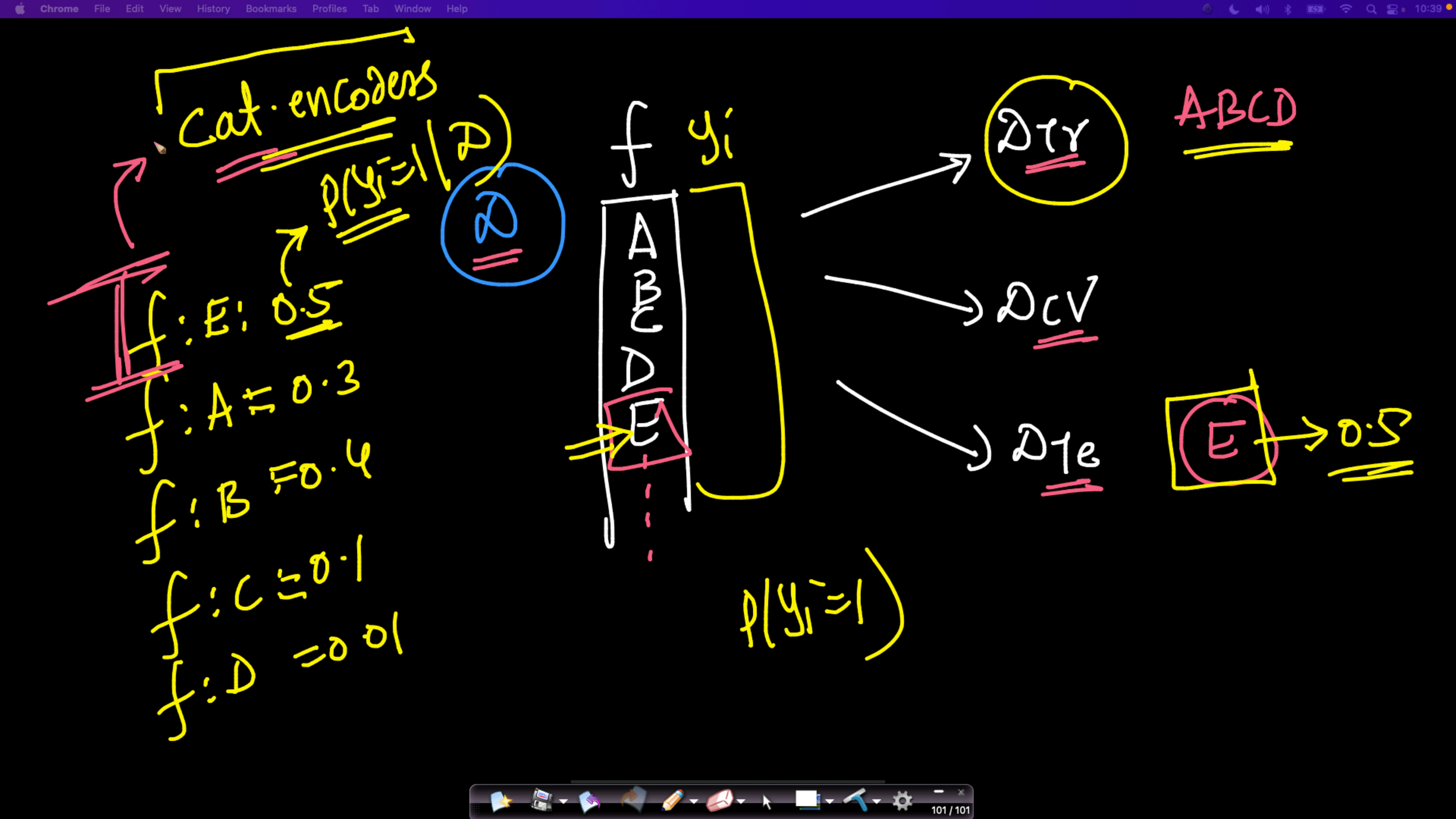
col. sampling




Chrome File Edit View History Bookmarks Profiles Tab Window Help
10:33
100 / 100


Chrome File Edit View History Bookmarks Profiles Tab Window Help
10:33
100 / 100


If f10 + ...
100
10
f10
~10
CSR = 0.1
non-zero
90
zero
100 Trees
If f12 + ...
10
f12
~10
non-zero
90
zero


Cat. encoders
P(yi=1|D)
D
f : E : 0.5
f : A = 0.3
f : B = 0.4
f : C = 0.1
f : D = 0.01
f
yi
A
B
E
D
E
D1Y
D1V
D1e
ABCD
E
0.5
P(yi=1)

fi

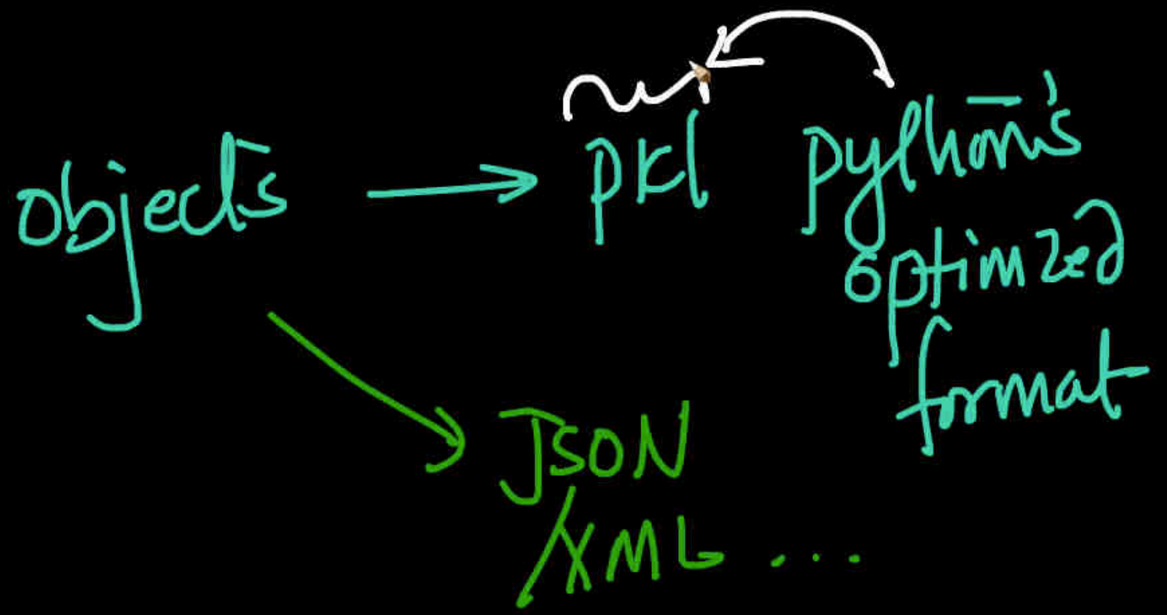
Target enloder : encoder ; - - -

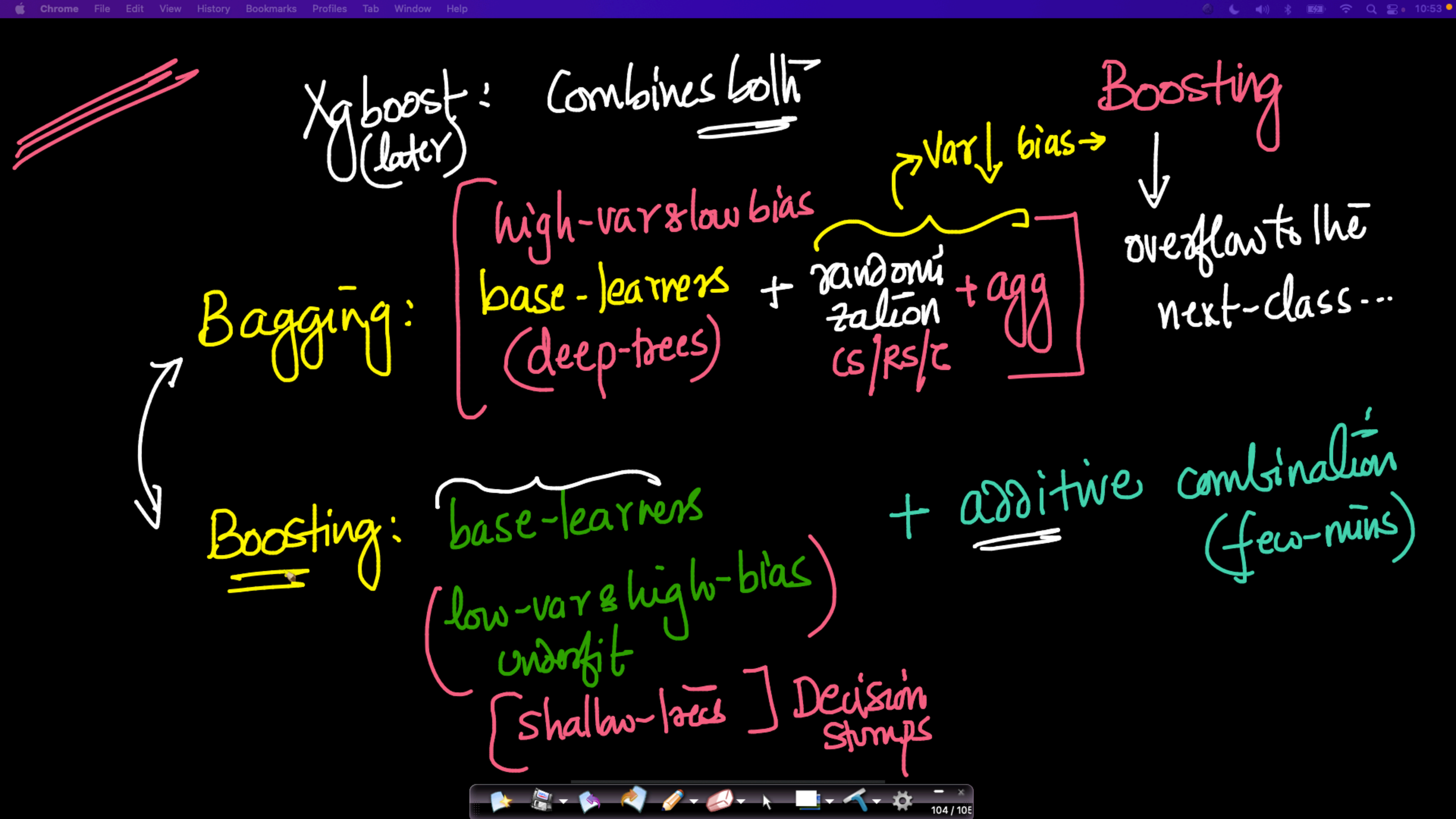
→ object

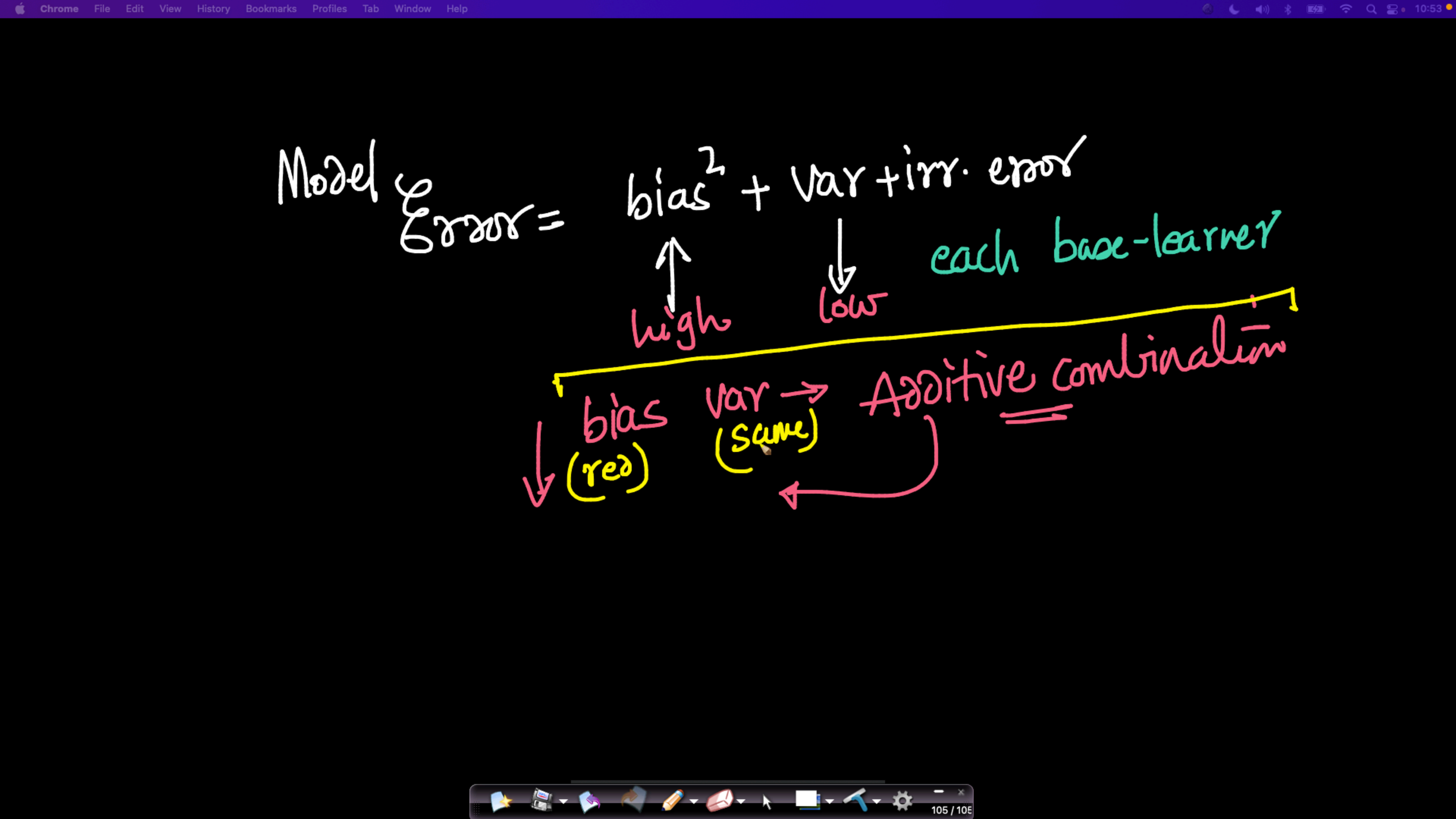
↓

{ strc it
toaisk

pid file




Xgboost: Combines both
(later)
Bagging:
high-var & low bias
base-learners
(deep-trees)
+ randomization
cs/rs/t
+ agg
Var↓ bias→
Boosting
overflow to the next-class...
Boosting:
base-learners
(low-var & high-bias)
underfit
[shallow-trees] Decision Stumps
+ additive combination
(few-runs)


Model Error = bias² + var + irr. error
high
low
each base-learner
bias (red)
var (same)
Additive combination

Chrome File Edit View History Bookmarks Profiles Tab Window Help

Core-idea: Frame-work

$$D_{tr} = \{(x_i, y_i)\}_{i=1}^{n}$$ (real)

easier to grasp

regression

Classify: post read

Stage 0 : M_0 = Mean-model

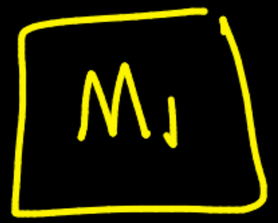
$$\hat{y}_i = \text{mean}(y_i s)$$

$h_0(x)$

$$y_i - \hat{y}_i^0 = \text{error}_i^0 \quad \forall i = 1 \to n$$

106 / 108

Stage 1:



Shallow DT (extreme: Decision Stump)

$h_1(x)$

$\{x_i, err_i\}$

y_i's

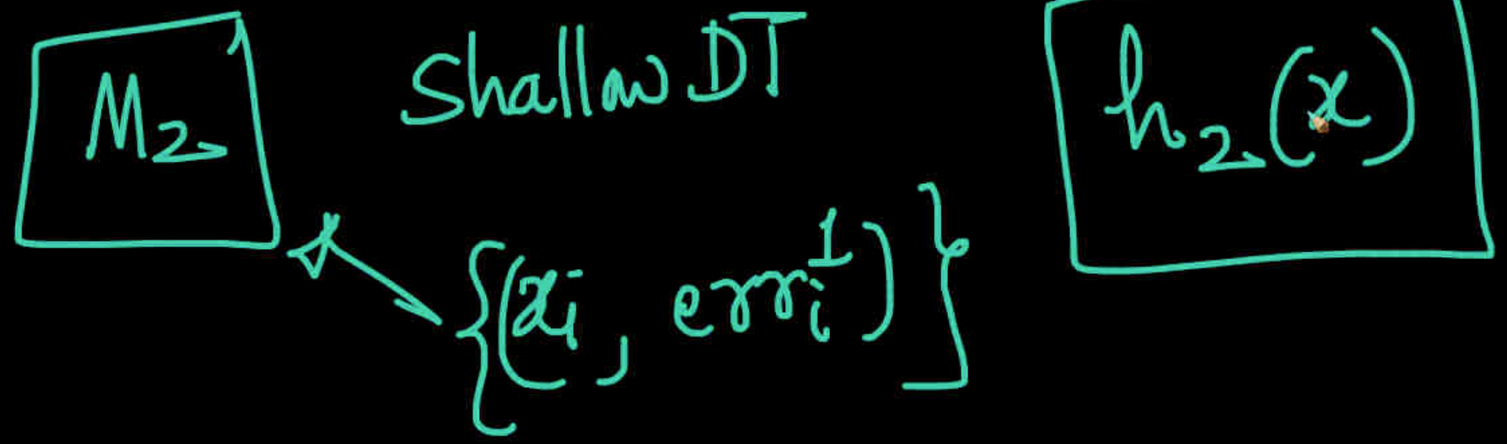
$$F_1(x) = \alpha_0 h_0(x) + \alpha_1 h_1(x)$$

model after stage 1

algo to find α_0 & α_1

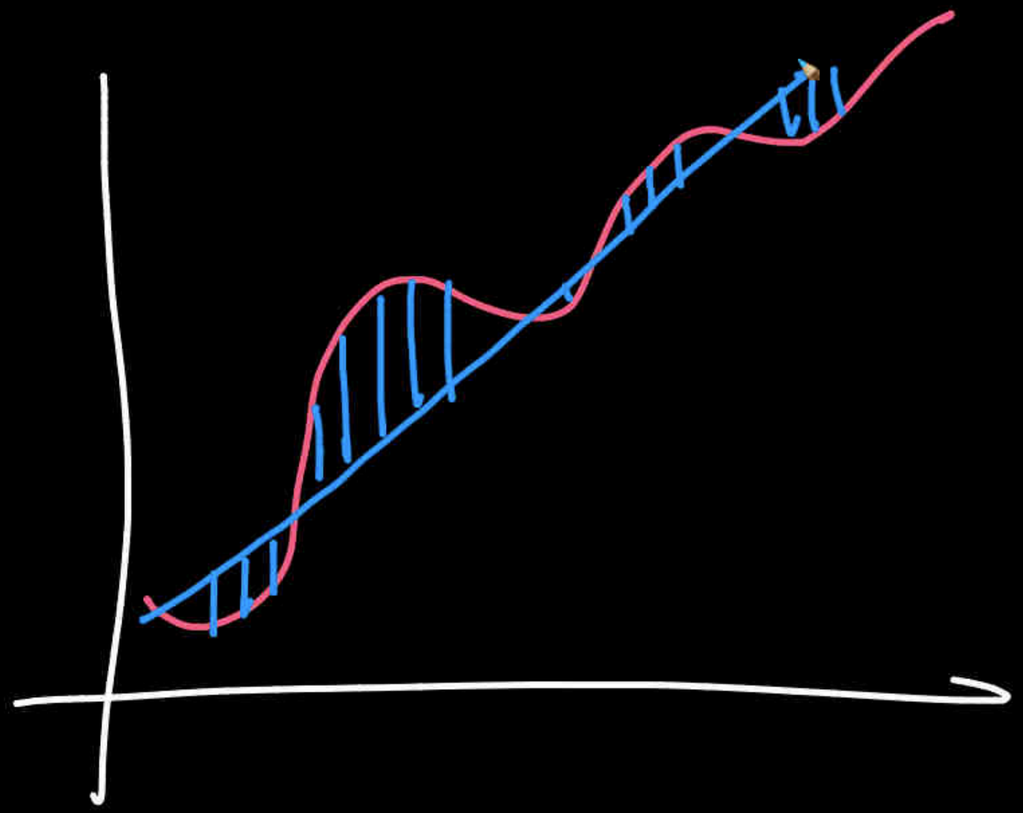
$$y_i - f_1(x_i) = err_i^1 \qquad \forall i : 1 \to n$$

Stage 2:



$$F_2(x) = \alpha_0 h_0(x) + \alpha_1 h_1(x) + \alpha_2 h_2(x)$$

Model after stage 2



repeat ....

{ M-Stages!

$$F_M(x) = \sum_{i=0}^{M} \alpha_i h_i(x)$$

mean for $h_0(x)$

shallow DT

optimization to find α_i

Boosting:- each α_i is learnt @ different time

$$F_m(x) = \sum_{i=0}^{M} \alpha_i h_i(x)$$

Boosting ⟹ additive weighted model

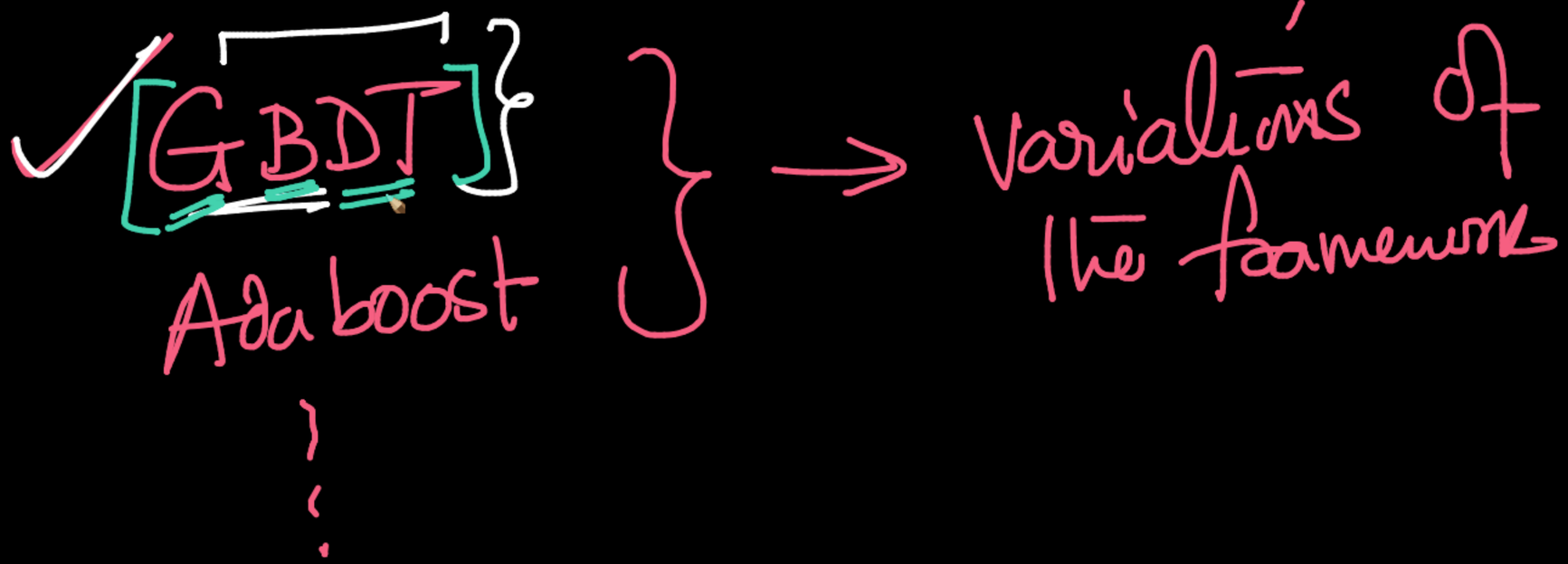
Lr. reg :-

$$F(x) = \sum_{i=1}^{d} w_i x_i + w_0$$

GD : all w_i's are learnt @ same time

err_i^j = errors after stage j

↑ "residuals"


GBDT
Adaboost
Variations of the framework

detour

$$F_K(x) = \sum_{i=0}^{K} \alpha_i h_i(x)$$

$$\mathcal{D}^{Tr} = \{(x_i, y_i)\}_{i=1}^{n}$$

Residuals

Loss-fns:

Gradients

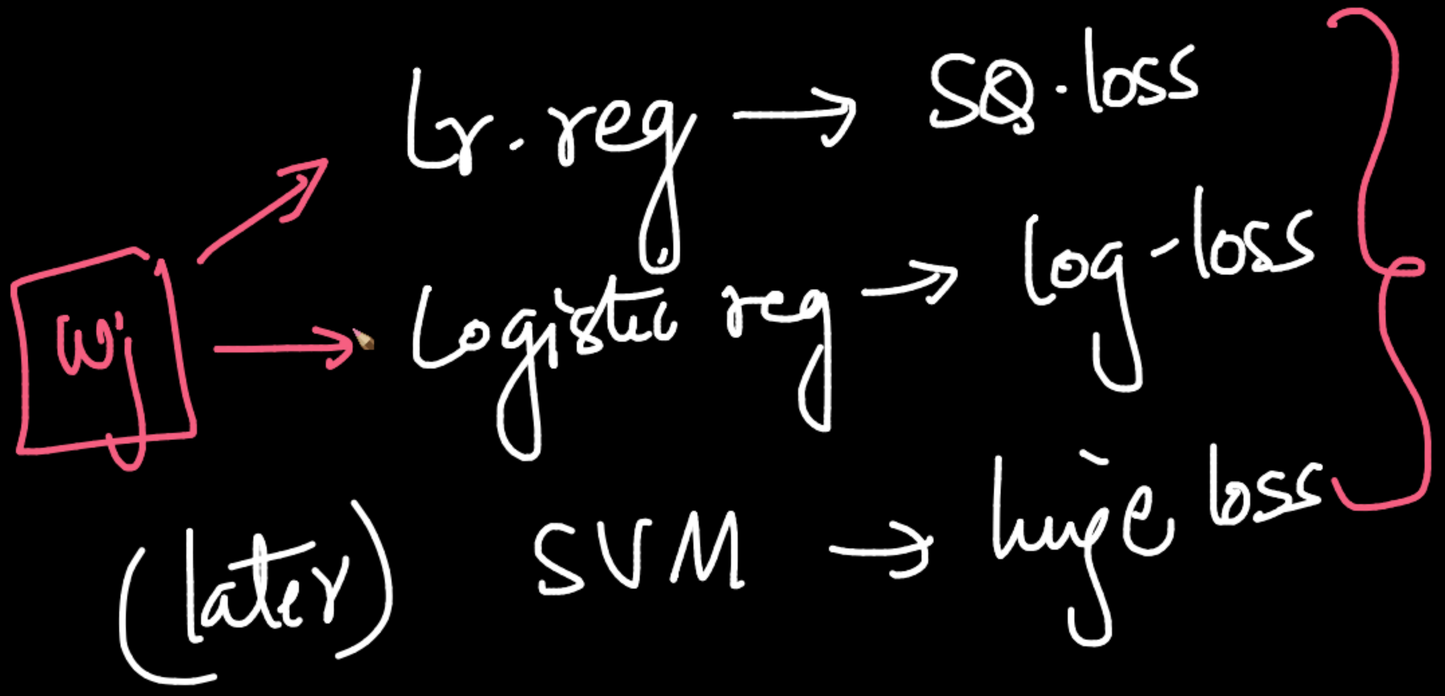
pseudo-residuals

GBDT

[any diff loss-function]

[sq-loss : reg]

Post read [log-loss : Classfn]


lr. reg → SQ. loss
Logistic reg → log-loss
(later) SVM → huge loss

e.g: sq. loss

$\hat{y}_i$: predicted

actual y_i

$$\mathcal{L}^{sq}(y_i, F_k(x_i)) = (y_i - F_k(x_i))^2$$

$$\frac{\partial \mathcal{L}^{sq}}{\partial F_k(x_i)} = (-1) \cdot 2 \cdot (y_i - F_k(x_i))$$

$$= -2 (y_i - F_k(x_i))$$

$$-\frac{\partial \mathcal{L}^{SQ}}{\partial F_k(x_i)} = 2\left(y_i - F_k(x_i)\right)$$

$$\text{error}_i^k = \text{res}_{i,k} \quad (\gamma_{ik})$$

pseudo residual

neg. grad = residual

Can prove for log-loss also → little more Math...

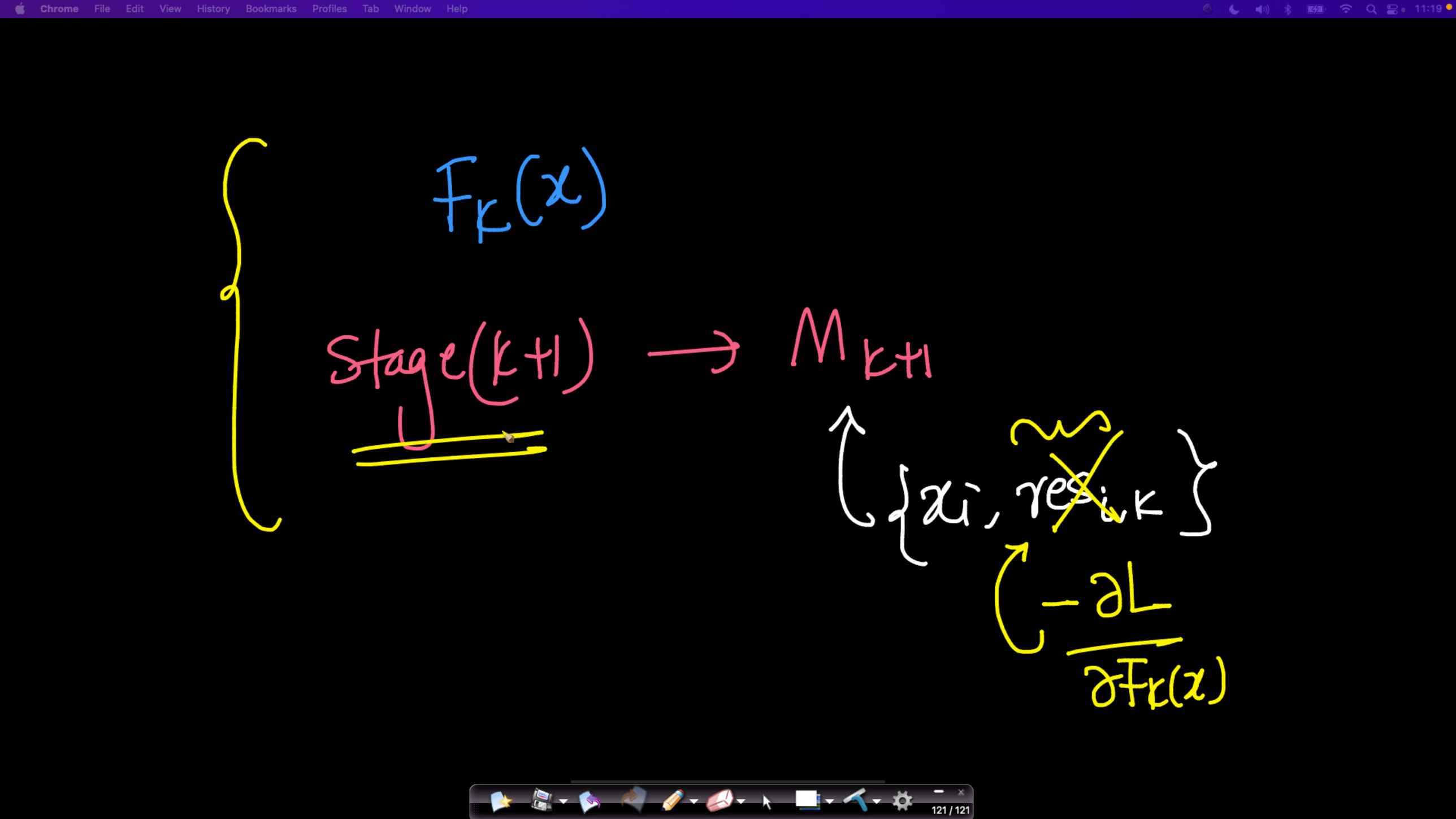
(Classfn)

$$\text{neg.grad} = \frac{-\partial L^{\log}}{\partial F_t(x_i)} = y_i - p_i$$

$\mathcal{L}$: differentiable - loss fn

$$-\frac{\partial \tilde{\mathcal{L}}}{\partial f_k(x_i)} = \text{residual}_{i,k}$$

→ error


$F_k(x)$
Stage(k+1)
M_{k+1}
$\{x_i, res_{i,k}\}$
$-\frac{\partial L}{\partial F_k(x)}$

To train $k+1^{th}$ base-model:

$$\left\{ x_i, -\frac{\partial L}{\partial F_k(x_i} \right\}$$

train on residuals
≈ train on
pseudo residuals

Boosting → neg. grad as pseudo residual

↓

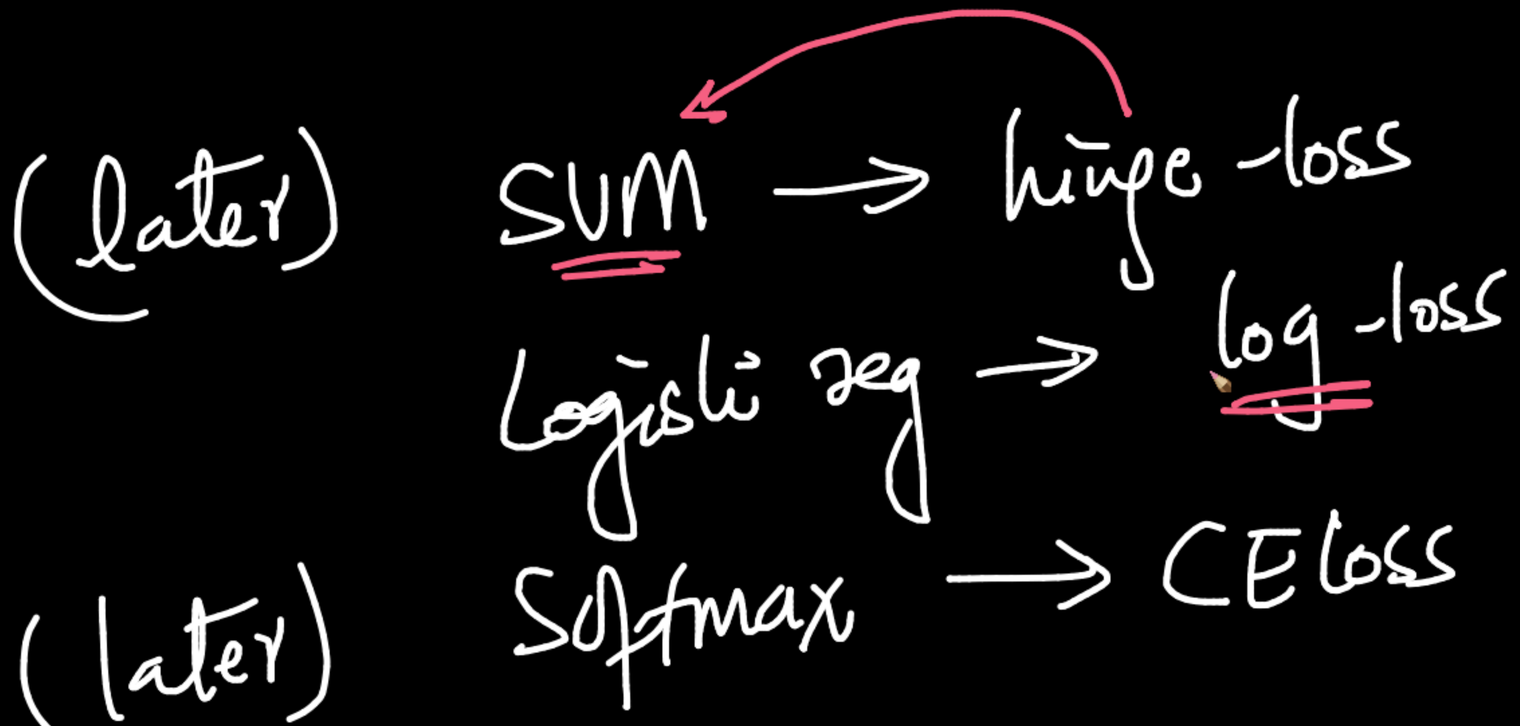
instead of the residual/error

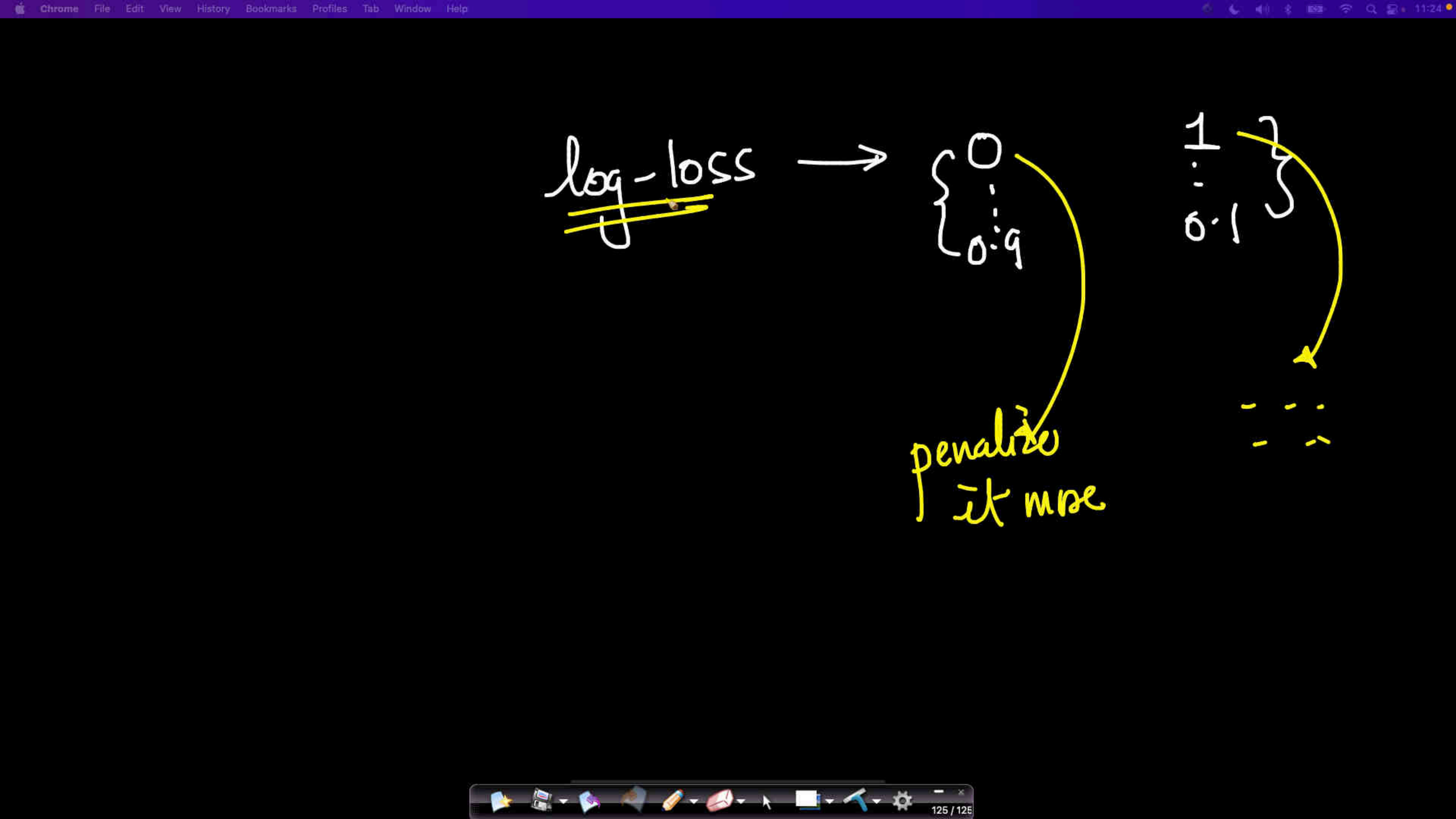
↓

{GBDT} → why is this popular

↳ Loss fn of my choice

Flexibility


(later)
SVM → hinge-loss
Logistic reg → log-loss
(later)
Softmax → CE loss


log-loss
0
0:9
1
0.1
penalize it more

Reg

$(y_i - \hat{y}_i)^2$

- sq. loss → lr. reg
- [abs. loss]
- $(y_i - \hat{y}_i)^4$ → much more penalization of errors

however, i.e. when the set $\mathcal{H}$ is finite, we choose the candidate function h closest to the gradient of L for which the coefficient γ may then be calculated with the aid of line search on the above equations. Note that this approach is a heuristic and therefore doesn't yield an exact solution to the given problem, but rather an approximation. In pseudocode, the generic gradient boosting method is:[5][2]

Input: training set $\{(x_i, y_i)\}_{i=1}^{n}$, a differentiable loss function $L(y, F(x))$, number of iterations M.

Algorithm:

1. Initialize model with a constant value:

$$F_0(x) = \arg\min_{\gamma} \sum_{i=1}^{n} L(y_i, \gamma).$$

2. For m = 1 to M:
    1. Compute so-called *pseudo-residuals*:

$$r_{im} = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)} \quad \text{for } i = 1, \ldots, n.$$

    2. Fit a base learner (or weak learner, e.g. tree) closed under scaling $h_m(x)$ to pseudo-residuals, i.e. train it using the training set $\{(x_i, r_{im})\}_{i=1}^{n}$.
    3. Compute multiplier γ_m by solving the following one-dimensional optimization problem:

$$\gamma_m = \arg\min_{\gamma} \sum_{i=1}^{n} L\left(y_i, F_{m-1}(x_i) + \gamma h_m(x_i)\right).$$

    4. Update the model:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x).$$

3. Output $F_M(x)$.

Gradient tree bo

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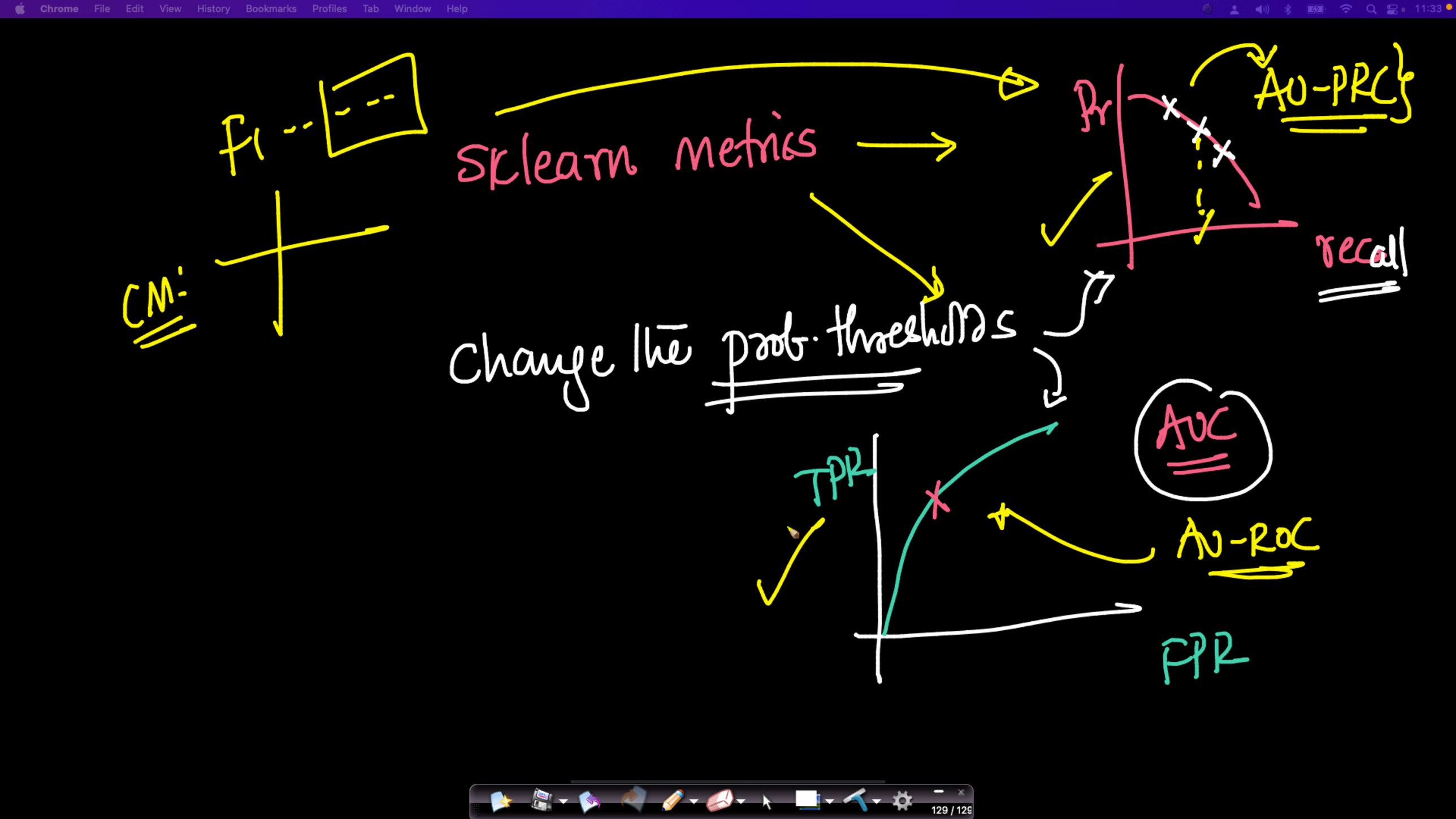
Gradient tree boosting [edit]

Gradient boosting is typi… d size as base learners. For this special case,

Amazon


F1
CM:
sklearn metrics
Pr
Au-PRC
recall
Change the prob. thresholds
TPR
FPR
AUC
Au-RoC

$(x_i, y_i) \longrightarrow$ mean $h_0(x) \xrightarrow{err_i^0} h_1(x)$; $\alpha_0 h_0(x) + \alpha_1 h_1(x) = F_1(x)$

err_i^1

$h_2(x)$

$\alpha_0 h_0(x) + \alpha_1 h_1(x) + \alpha_2 h_2(x)$

$$err_i^j = y_i - F_j(x)$$

M base learners

```
clf = DecisionTreeClassifier(random_state=0, max_depth=1_best, class_weight={ 0:0.1, 1:w } )
clf.fit(X_train, y_train)

y_pred_val = clf.predict(X_val)
val_score = f1_score(y_val, y_pred_val)

print(val_score)

confusion_matrix(y_val, y_pred_val)
```

```
2
0.41618497109826585
array([[157,  87],
       [ 14,  36]])
```

```
# Feature importance
importances = clf.feature_importances_
indices = np.argsort(importances)[::-1] # Sort feature importances in descending order
names = [X_train.columns[i] for i in indices] # Rearrange feature names so they match the sorted feature importance
plt.figure(figsize=(15, 7)) # Create plot
plt.title("Feature Importance") # Create plot title
plt.bar(range(X_train.shape[1]), importances[indices]) # Add bars
plt.xticks(range(X_train.shape[1]), names, rotation=90) # Add feature names as x-axis labels
plt.show() # Show plot
```

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