Tabular Model

Tabular model yordamida Loan decision (portfolio uchun qo`shimcha kichik loyiha)

Ma`lumotlarga qarab kimlarga kredit ajratish haqida qaror qabul qilish.

Dataset: Loan Default

```
df = pd.read_csv('Loan_Default.csv')
df.head()
```

	ID	year	loan_limit	Gender	approv_in_adv	loan_type	loan_purpose	Credit_Worthiness	open_credit	busine
0	24890	2019	cf	Sex Not Available	nopre	type1	p1	l1	nopc	
1	24891	2019	cf	Male	nopre	type2	p1	l1	nopc	
2	24892	2019	cf	Male	pre	type1	p1	l1	nopc	
3	24893	2019	cf	Male	nopre	type1	p4	l1	nopc	
4	24894	2019	cf	Joint	pre	type1	p1	l1	nopc	

5 rows × 34 columns

datamizni ko`zdan kechirib olamiz:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 148670 entries, 0 to 148669
Data columns (total 34 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   ID                        148670 non-null  int64
 1   year                      148670 non-null  int64
 2   loan_limit                145326 non-null  object
 3   Gender                    148670 non-null  object
 4   approv_in_adv             147762 non-null  object
 5   loan_type                 148670 non-null  object
 6   loan_purpose              148536 non-null  object
 7   Credit_Worthiness         148670 non-null  object
 8   open_credit               148670 non-null  object
 9   business_or_commercial    148670 non-null  object
 10  loan_amount               148670 non-null  int64
```

```
 11  rate_of_interest           112231 non-null  float64
 12  Interest_rate_spread       112031 non-null  float64
 13  Upfront_charges            109028 non-null  float64
 14  term                       148629 non-null  float64
 15  Neg_ammortization          148549 non-null  object
 16  interest_only              148670 non-null  object
 17  lump_sum_payment           148670 non-null  object
 18  property_value             133572 non-null  float64
 19  construction_type          148670 non-null  object
 20  occupancy_type             148670 non-null  object
 21  Secured_by                 148670 non-null  object
 22  total_units                148670 non-null  object
 23  income                     139520 non-null  float64
 24  credit_type                148670 non-null  object
 25  Credit_Score               148670 non-null  int64
 26  co-applicant_credit_type   148670 non-null  object
 27  age                        148470 non-null  object
 28  submission_of_application  148470 non-null  object
 29  LTV                        133572 non-null  float64
 30  Region                     148670 non-null  object
 31  Security_Type              148670 non-null  object
 32  Status                     148670 non-null  int64
 33  dtir1                      124549 non-null  float64
dtypes: float64(8), int64(5), object(21)
memory usage: 38.6+ MB
```

```
# cat va cont ustunlarni ajratib olish:

# category columns
cat_name = []
# raqamli columns
cont_name = []

for col in df.columns:
  if df[col].dtype== object:
    cat_name.append(col)
  else :
    cont_name.append(col)


print(len(cont_name))
print(len(cat_name))
```

```
13
21
```

cont_name listdan "Status" ustunini olib tashlaymiz. chunki u bizga bashorat uchun kerak.

```
del cont_name[-2]
```

```
cont_name
```

```
['ID',
 'year',
 'loan_amount',
 'rate_of_interest',
 'Interest_rate_spread',
 'Upfront_charges',
 'term',
 'property_value',
 'income',
 'Credit_Score',
 'LTV',
 'dtir1']
```

```
from fastai.tabular.all import *

# path
path = Path('.')

# path.ls()

# dataloaders
dls = TabularDataLoaders.from_csv(path/'Loan_Default.csv', path=path, bs=64, y_names =
                                  cat_names = cat_name,
                                  cont_names = cont_name,
                                  procs = [FillMissing , Categorify, Normalize])


# train
learn = tabular_learner(dls, metrics=accuracy)

# tabular data uchun fit_one_cycle(), modelni o dan quradi
learn.fit_one_cycle(3)
```

epoch	train_loss	valid_loss	accuracy	time
0	0.003385	0.000403	0.749849	00:31
1	0.002944	0.000164	0.749849	00:25
2	0.002863	0.000242	0.749849	00:26

```
learn.show_results(max_n=64)
```

	loan_limit	Gender	approv_in_adv	loan_type	loan_purpose	Credit_Worthiness	open_credit	business_or_commercial
0	1.0	1.0	1.0	2.0	4.0	1.0	1.0	1.0

	loan_limit	Gender	approv_in_adv	loan_type	loan_purpose	Credit_Worthiness	open_credit	business_or_commercial
1	1.0	2.0	1.0	1.0	3.0	1.0	1.0	2.0
2	1.0	1.0	1.0	1.0	1.0	1.0	1.0	2.0
3	1.0	4.0	1.0	1.0	3.0	1.0	1.0	2.0
4	1.0	3.0	1.0	1.0	1.0	2.0	1.0	2.0
5	1.0	1.0	1.0	2.0	3.0	1.0	1.0	1.0
6	1.0	2.0	2.0	1.0	4.0	1.0	1.0	2.0
7	1.0	4.0	1.0	1.0	4.0	1.0	1.0	2.0
8	1.0	3.0	1.0	1.0	1.0	1.0	1.0	2.0
9	1.0	4.0	1.0	1.0	4.0	1.0	1.0	2.0
10	1.0	3.0	2.0	2.0	3.0	1.0	1.0	1.0
11	1.0	3.0	1.0	1.0	4.0	1.0	1.0	2.0
12	1.0	3.0	1.0	1.0	1.0	1.0	1.0	2.0
13	1.0	1.0	1.0	1.0	1.0	1.0	1.0	2.0
14	1.0	2.0	1.0	1.0	4.0	1.0	1.0	2.0
15	1.0	2.0	1.0	1.0	3.0	1.0	1.0	2.0
16	1.0	1.0	1.0	1.0	3.0	1.0	1.0	2.0
17	1.0	4.0	1.0	1.0	3.0	1.0	1.0	2.0
18	1.0	3.0	1.0	1.0	1.0	1.0	1.0	2.0
19	1.0	4.0	2.0	1.0	4.0	1.0	1.0	2.0
20	1.0	4.0	1.0	1.0	4.0	1.0	1.0	2.0
21	1.0	2.0	1.0	1.0	1.0	1.0	1.0	2.0
22	1.0	2.0	1.0	1.0	4.0	1.0	1.0	2.0
23	1.0	4.0	1.0	1.0	4.0	1.0	1.0	2.0
24	2.0	4.0	2.0	1.0	3.0	1.0	1.0	2.0
25	1.0	3.0	1.0	1.0	4.0	1.0	1.0	2.0
26	1.0	2.0	1.0	1.0	3.0	1.0	1.0	2.0
27	1.0	2.0	2.0	1.0	3.0	1.0	1.0	2.0
28	1.0	2.0	2.0	1.0	2.0	1.0	1.0	2.0
29	1.0	2.0	1.0	1.0	1.0	1.0	1.0	2.0
30	1.0	4.0	2.0	1.0	1.0	1.0	1.0	2.0
31	1.0	2.0	2.0	1.0	4.0	1.0	1.0	2.0
32	1.0	4.0	1.0	1.0	4.0	1.0	1.0	2.0
33	1.0	3.0	1.0	1.0	1.0	1.0	1.0	2.0
34	2.0	4.0	1.0	1.0	1.0	1.0	1.0	2.0
35	1.0	4.0	1.0	1.0	3.0	1.0	1.0	2.0
36	1.0	2.0	2.0	1.0	1.0	1.0	1.0	2.0
37	1.0	2.0	1.0	2.0	4.0	1.0	1.0	1.0
38	1.0	1.0	1.0	1.0	3.0	2.0	2.0	2.0

	loan_limit	Gender	approv_in_adv	loan_type	loan_purpose	Credit_Worthiness	open_credit	business_or_commercial
39	1.0	3.0	1.0	3.0	3.0	1.0	1.0	2.0
40	1.0	1.0	1.0	2.0	3.0	1.0	1.0	1.0
41	1.0	3.0	1.0	1.0	1.0	1.0	1.0	2.0
42	0.0	1.0	1.0	1.0	4.0	1.0	1.0	2.0
43	1.0	3.0	1.0	2.0	3.0	1.0	1.0	1.0
44	2.0	1.0	1.0	1.0	2.0	1.0	1.0	2.0
45	1.0	3.0	1.0	1.0	4.0	1.0	1.0	2.0
46	1.0	1.0	1.0	1.0	4.0	1.0	1.0	2.0
47	1.0	2.0	1.0	1.0	4.0	1.0	1.0	2.0
48	0.0	2.0	1.0	1.0	4.0	1.0	1.0	2.0
49	1.0	4.0	1.0	3.0	4.0	1.0	1.0	2.0
50	1.0	4.0	1.0	3.0	3.0	1.0	1.0	2.0
51	1.0	1.0	2.0	1.0	4.0	1.0	1.0	2.0
52	1.0	1.0	1.0	1.0	4.0	1.0	1.0	2.0
53	1.0	1.0	1.0	1.0	3.0	1.0	1.0	2.0
54	1.0	4.0	2.0	1.0	1.0	1.0	1.0	2.0
55	1.0	4.0	1.0	3.0	4.0	1.0	1.0	2.0
56	1.0	2.0	1.0	1.0	4.0	1.0	1.0	2.0
57	1.0	4.0	1.0	1.0	1.0	1.0	1.0	2.0
58	1.0	2.0	1.0	1.0	4.0	1.0	1.0	2.0
59	1.0	3.0	1.0	2.0	4.0	1.0	1.0	1.0
60	1.0	3.0	1.0	1.0	4.0	1.0	1.0	2.0
61	1.0	1.0	1.0	1.0	4.0	1.0	1.0	2.0
62	1.0	3.0	1.0	1.0	1.0	1.0	1.0	2.0
63	1.0	2.0	1.0	1.0	3.0	1.0	1.0	2.0