analysis_lead_scoring_predictor

August 12, 2022

1 Lead Scoring Predictor

https://drive.google.com/drive/folders/1gpRgYS7QhZ6k9kJJwFGm4QPEPBa_r_3e

L'objectif du cas est de proposer un algorithme de scoring de nos leads entrants, avec les données qui te sont mises à disposition. Le résultat en lui-même nous intéresse peu, nous évaluerons plutôt la démarche générale et la qualité du travail mené. Pour t'aider dans le déroulé du cas, nous te proposons la trame suivante : 1. Analyse des données à disposition 2. Proposition d'un algorithme de Lead Scoring 3. Proposition de données additionnelles que tu aurais aimé avoir pour améliorer l'algorithme 4. Quelles applications pour cet algorithme chez Ornikar ?

Tu peux créer la solution dans le langage de ton choix, tant que c'est l'un de tes langages de prédilection. Le format de restitution est libre.

Bon courage !

La team Data Ornikar

[1]:
```
import json
import pickle
import warnings

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn import svm

from sklearn.model_selection import GridSearchCV
from sklearn.inspection import permutation_importance
```

```
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score, f1_score

from pandas.core.common import SettingWithCopyWarning

COLORS = sns.color_palette('muted')
FIGSIZE = (10,7)
warnings.simplefilter(action="ignore", category=SettingWithCopyWarning)
```

[2]:
```
def predict_evaluate(predictor, X_train, y_train, X_test, y_test,␣
↪response=False):
    """Predict and evaluate predictor."""
    y_test_predicted = predictor.predict(X_test)

    train_acc = predictor.score(X_train, y_train)
    test_acc = predictor.score(X_test, y_test)
    f1_s = f1_score(y_test, y_test_predicted)

    if response:
        return (train_acc, test_acc, f1_s)
    else:
        print(f"Predictor train accuracy: {train_acc:.3f}")
        print(f"Predictor test accuracy: {test_acc:.3f}")
        print(f"Predictor f1 score: {f1_s:.3f}")

        print(confusion_matrix(y_test, y_test_predicted))
        print(classification_report(y_test, y_test_predicted))
```

2 1. Analyse des données

[3]:
```
quotes = pd.read_csv('data/long_quotes.csv')
logs = pd.read_csv('data/mixpanel.csv')
```

1.1 Quotes analysis

[4]:
```
quotes.head(3)
```

[4]:
```
         long_quote_id              lead_id country_code first_utm_source  \
0  7527452923606463240 -1065398551916348537           FR              NaN
1  2676593580459190130 -3188174584045372774           FR              NaN
2 -8181351603970286153   809161028469555575           FR              NaN

  last_utm_source  has_been_proposed_formulas  has_chosen_formula  \
0             NaN                       False               False
1             NaN                       False               False
2             NaN                       False               False
```

```
   has_subscribed_online             submitted_at effective_start_date  …  \
0                  False  2021-09-01 18:18:19 UTC           2021-09-05  …
1                  False  2021-09-01 12:29:25 UTC           2021-09-03  …
2                  False  2021-09-01 03:52:34 UTC           2021-11-01  …

  main_driver_age main_driver_gender main_driver_licence_age  \
0           40-59                  M                     15+
1           40-59                  F                     15+
2           40-59                  M                     15+

  main_driver_bonus vehicle_age vehicle_class vehicle_group  \
0           064-084       03-05           I-K         31-32
1               050       10-14           I-K         29-30
2               100          00           O-R           35+

      vehicle_region has_secondary_driver has_subscribed
0           Picardie                False          False
1        Rhone-Alpes                 True          False
2  Champagne-Ardenne                 True          False

[3 rows x 33 columns]
```

[5]:
```
quotes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1215 entries, 0 to 1214
Data columns (total 33 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   long_quote_id               1215 non-null   int64
 1   lead_id                     1215 non-null   int64
 2   country_code                1215 non-null   object
 3   first_utm_source            232 non-null    object
 4   last_utm_source             232 non-null    object
 5   has_been_proposed_formulas  1215 non-null   bool
 6   has_chosen_formula          1215 non-null   bool
 7   has_subscribed_online       1215 non-null   bool
 8   submitted_at                1215 non-null   object
 9   effective_start_date        1214 non-null   object
 10  rbs_result                  50 non-null     object
 11  provider                    1027 non-null   object
 12  product_third_party         1027 non-null   object
 13  product_intermediate        1027 non-null   object
 14  product_all_risks           1022 non-null   object
 15  annual_price_third_party    1027 non-null   object
 16  annual_price_intermediate   1027 non-null   object
 17  annual_price_all_risks      1022 non-null   object
 18  chosen_formula              286 non-null    object
```

```
 19  chosen_product              286 non-null    object
 20  policy_subscribed_at        23 non-null     object
 21  contract_id                 17 non-null     float64
 22  payment_frequency           0 non-null      float64
 23  main_driver_age             1215 non-null   object
 24  main_driver_gender          1215 non-null   object
 25  main_driver_licence_age     1215 non-null   object
 26  main_driver_bonus           1215 non-null   object
 27  vehicle_age                 1215 non-null   object
 28  vehicle_class               1199 non-null   object
 29  vehicle_group               1199 non-null   object
 30  vehicle_region              1215 non-null   object
 31  has_secondary_driver        1215 non-null   bool
 32  has_subscribed              1215 non-null   bool
dtypes: bool(5), float64(2), int64(2), object(24)
memory usage: 271.8+ KB
```

Duplicates rows in the quotes

[6]:
```
quotes['long_quote_id'].value_counts()
```

[6]:
```
 3193278899385012716    2
-2567510670073880055    2
-6207503491702107433    2
-8460876607405465288    1
-5823080703452367928    1
                       ..
-7247650444290653422    1
 5915931168270183226    1
 5511888581927997971    1
-3740565721924245756    1
-4400907979771225928    1
Name: long_quote_id, Length: 1212, dtype: int64
```

[7]:
```
quotes = quotes.drop_duplicates()
```

[8]:
```
quotes['long_quote_id'].value_counts()
```

[8]:
```
-8460876607405465288    1
-8999035888099581211    1
 2676593580459190130    1
-2080494545874085595    1
-7023964638711598666    1
                       ..
 5915931168270183226    1
 5511888581927997971    1
-3740565721924245756    1
 5851731705011274421    1
```

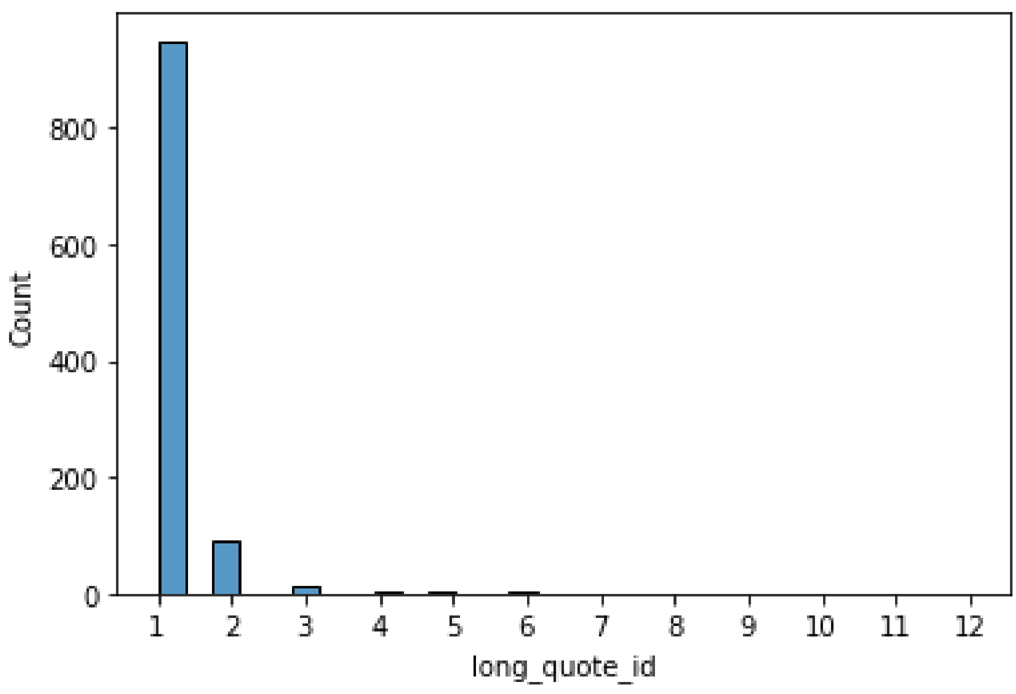
```
-4400907979771225928    1
Name: long_quote_id, Length: 1212, dtype: int64
```

[9]:
```python
quotes['lead_id'].value_counts()
```

[9]:
```
 6007475069273989421    12
 707106108801747155      6
 2985704236974667725     6
 7443518922044095226     5
 6417788977143244366     5
                        ..
 4864065490631433717     1
-3314367315040936652     1
 3837605510687758841     1
 3350398049064773035     1
-2208476976128241344     1
Name: lead_id, Length: 1058, dtype: int64
```

[10]:
```python
df_gb = quotes.groupby(['lead_id'])['long_quote_id'].agg('count').reset_index()
```

[11]:
```python
sns.histplot(data=df_gb, x='long_quote_id', bins=30)
_ = plt.xticks([i for i in range(1,13)])
```

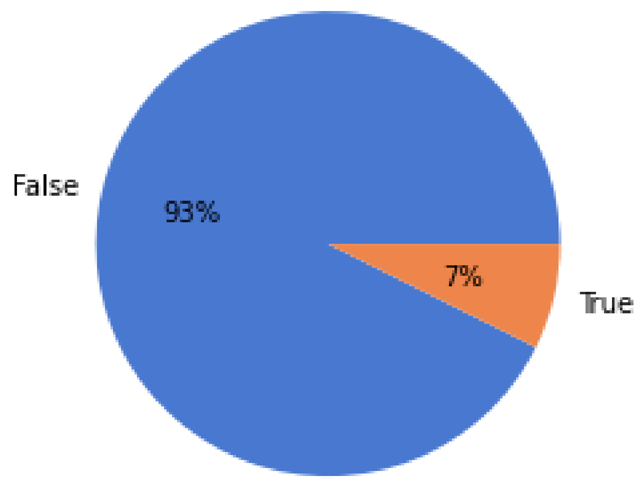


Feature has_subscribed is unbalanced

[12]:
```
print(quotes['has_subscribed'].value_counts())

plt.pie(quotes['has_subscribed'].value_counts(),
 ↪labels=set(quotes['has_subscribed']), colors=COLORS, autopct='%.0f%%')
plt.show()
```

```
False    1123
True       89
Name: has_subscribed, dtype: int64
```

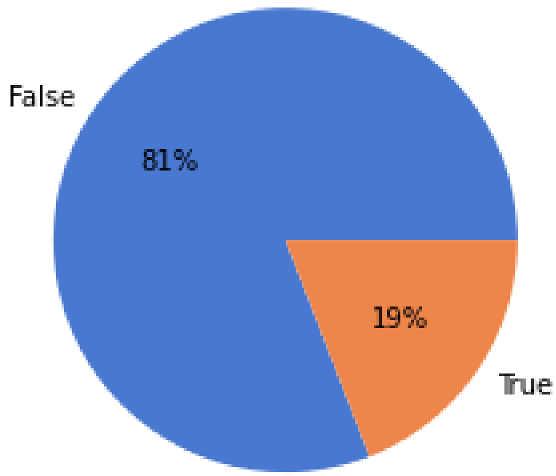


Most of subscription comes from Customer Care

[13]:
```
quotes_subscribed = quotes[quotes['has_subscribed']==True]
print(quotes_subscribed['has_subscribed_online'].value_counts())

plt.pie(quotes_subscribed['has_subscribed_online'].value_counts(),
 ↪labels=set(quotes_subscribed['has_subscribed_online']), colors=COLORS,
 ↪autopct='%.0f%%')
plt.show()
```

```
False    72
True     17
Name: has_subscribed_online, dtype: int64
```



1.2 Logs analysis

[14]:
```
logs.head(5)
```

[14]:
```
                  time                                           page_view  \
0  2021-09-01 18:31:02  {"page_collection":"website","page_path":"/ass…
1  2021-09-01 18:31:02  {"page_collection":"website","page_path":"/ass…
2  2021-09-01 14:15:49  {"page_collection":"website","page_path":"/ass…
3  2021-09-01 14:16:29  {"page_collection":"website","page_path":"/ass…
4  2021-09-01 14:16:29  {"page_collection":"website","page_path":"/ass…

     mp_os      mp_browser utm_source  \
0  Android  Android Mobile        NaN
1  Android  Android Mobile        NaN
2  Windows         Firefox     google
3  Windows         Firefox     google
4  Windows         Firefox     google

                              insurance_subscription  \
0  {"lead_quote_status": "NoGo", "nogo_reason": "…
1  {"lead_quote_status": "NoGo", "nogo_reason": "…
2  {"broker_name": null, "category_quoted_tiers":…
3  {"broker_name": null, "long_quote_id": -716719…
4  {"broker_name": null, "long_quote_id": -716719…

                              mp_event_name
0  Insurance - Complete Insurance Long Quote
```

```
1  Insurance - Complete Insurance Long Quote
2  Insurance - Complete Insurance Long Quote
3   Insurance - Customize Insurance Contract
4   Insurance - Customize Insurance Contract
```

[15]:

```
logs.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9410 entries, 0 to 9409
Data columns (total 7 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   time                    9410 non-null   object
 1   page_view               9410 non-null   object
 2   mp_os                   9410 non-null   object
 3   mp_browser              9410 non-null   object
 4   utm_source              6830 non-null   object
 5   insurance_subscription  9410 non-null   object
 6   mp_event_name           9410 non-null   object
dtypes: object(7)
memory usage: 514.7+ KB
```

[16]:

```
logs_parsed = pd.io.json.json_normalize(logs['insurance_subscription'].
↪apply(json.loads))
```

```
<ipython-input-16-81a4abc42ea3>:1: FutureWarning: pandas.io.json.json_normalize
is deprecated, use pandas.json_normalize instead
  logs_parsed =
pd.io.json.json_normalize(logs['insurance_subscription'].apply(json.loads))
```

[17]:

```
logs_parsed.head()
```

[17]:

```
  lead_quote_status                           nogo_reason broker_name  \
0              NoGo  Tarification impossible () EXCLUSION         NaN
1              NoGo  Tarification impossible () EXCLUSION         NaN
2                Go                                   NaN        None
3               NaN                                   NaN        None
4               NaN                                   NaN        None

  category_quoted_tiers  long_quote_id product_name product_type warranties  \
0                   NaN            NaN          NaN          NaN        NaN
1                   NaN            NaN          NaN          NaN        NaN
2                 autre  -7.167195e+18          NaN          NaN        NaN
3                   NaN  -7.167195e+18        autre  third_party         []
4                   NaN  -7.167195e+18        autre  third_party         []

   lead_id category_started vehicle_search_method  contract_id start_date
0      NaN              NaN                   NaN          NaN        NaN
```

```
1       NaN              NaN                    NaN          NaN        NaN
2       NaN              NaN                    NaN          NaN        NaN
3       NaN              NaN                    NaN          NaN        NaN
4       NaN              NaN                    NaN          NaN        NaN
```

[18]:
```python
logs_parsed = logs_parsed[logs_parsed['long_quote_id'].notnull()]
logs_parsed['long_quote_id'] = logs_parsed['long_quote_id'].astype('Int64').
 ↪astype(str)
```

3 2. Lead scoring predictor

3.0.1 Data prep

[19]:
```python
quotes.head(3)
```

[19]:
```
         long_quote_id              lead_id country_code first_utm_source  \
0  7527452923606463240 -1065398551916348537           FR              NaN
1  2676593580459190130 -3188174584045372774           FR              NaN
2 -8181351603970286153   809161028469555575           FR              NaN

  last_utm_source  has_been_proposed_formulas  has_chosen_formula  \
0             NaN                       False               False
1             NaN                       False               False
2             NaN                       False               False

   has_subscribed_online             submitted_at effective_start_date  …  \
0                  False  2021-09-01 18:18:19 UTC           2021-09-05  …
1                  False  2021-09-01 12:29:25 UTC           2021-09-03  …
2                  False  2021-09-01 03:52:34 UTC           2021-11-01  …

  main_driver_age main_driver_gender main_driver_licence_age  \
0           40-59                  M                     15+
1           40-59                  F                     15+
2           40-59                  M                     15+

  main_driver_bonus vehicle_age vehicle_class vehicle_group  \
0           064-084       03-05           I-K         31-32
1               050       10-14           I-K         29-30
2               100          00           O-R           35+

      vehicle_region has_secondary_driver has_subscribed
0           Picardie                False          False
1        Rhone-Alpes                 True          False
2  Champagne-Ardenne                 True          False

[3 rows x 33 columns]
```

[20]:
```
quotes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1212 entries, 0 to 1214
Data columns (total 33 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   long_quote_id               1212 non-null   int64
 1   lead_id                     1212 non-null   int64
 2   country_code                1212 non-null   object
 3   first_utm_source            229 non-null    object
 4   last_utm_source             229 non-null    object
 5   has_been_proposed_formulas  1212 non-null   bool
 6   has_chosen_formula          1212 non-null   bool
 7   has_subscribed_online       1212 non-null   bool
 8   submitted_at                1212 non-null   object
 9   effective_start_date        1211 non-null   object
 10  rbs_result                  50 non-null     object
 11  provider                    1025 non-null   object
 12  product_third_party         1025 non-null   object
 13  product_intermediate        1025 non-null   object
 14  product_all_risks           1020 non-null   object
 15  annual_price_third_party    1025 non-null   object
 16  annual_price_intermediate   1025 non-null   object
 17  annual_price_all_risks      1020 non-null   object
 18  chosen_formula              286 non-null    object
 19  chosen_product              286 non-null    object
 20  policy_subscribed_at        23 non-null     object
 21  contract_id                 17 non-null     float64
 22  payment_frequency           0 non-null      float64
 23  main_driver_age             1212 non-null   object
 24  main_driver_gender          1212 non-null   object
 25  main_driver_licence_age     1212 non-null   object
 26  main_driver_bonus           1212 non-null   object
 27  vehicle_age                 1212 non-null   object
 28  vehicle_class               1196 non-null   object
 29  vehicle_group               1196 non-null   object
 30  vehicle_region              1212 non-null   object
 31  has_secondary_driver        1212 non-null   bool
 32  has_subscribed              1212 non-null   bool
dtypes: bool(5), float64(2), int64(2), object(24)
memory usage: 280.5+ KB
```

[21]:
```
# To consider ? : first_utm_source, last_utm_source, submitted_at,␣
↪effective_start_date?,
quotes_categorical_cols = ['has_been_proposed_formulas', 'has_chosen_formula',␣
↪'provider', 'product_third_party',
```

```
                               'product_intermediate', 'product_all_risks',␣
↪'annual_price_third_party',
                               'annual_price_intermediate',␣
↪'annual_price_all_risks', 'chosen_formula', 'chosen_product',
                               'main_driver_age', 'main_driver_gender',␣
↪'main_driver_licence_age', 'main_driver_bonus',
                               'vehicle_age', 'vehicle_class', 'vehicle_group',␣
↪'vehicle_region', 'has_secondary_driver']

quotes_target_col = 'has_subscribed'
```

[22]:
```
X_quotes = quotes[quotes_categorical_cols]
y_quotes = quotes[quotes_target_col]
y_quotes = np.where(y_quotes==False, 0, 1)
```

[23]:
```
y_quotes
```

[23]:
```
array([0, 0, 0, …, 0, 1, 1])
```

[24]:
```
def clean_preprocess(df):
    """Replace missing values and get dumies for cat variables."""
    # provider, product_third_party, product_intermediate, product_all_risks,
    # annual_price_third_party, annual_price_intermediate,␣
↪annual_price_all_risks: replace by most frequent
    # chosen_formula, chosen_product : replace nans by 'not clicked'

    # Replacing missing values by most frequent
    df['provider'] = df['provider'].fillna(df['provider'].value_counts().
↪idxmax())
    df['product_third_party'] = df['product_third_party'].
↪fillna(df['product_third_party'].value_counts().idxmax())
    df['product_intermediate'] = df['product_intermediate'].
↪fillna(df['product_intermediate'].value_counts().idxmax())
    df['product_all_risks'] = df['product_all_risks'].
↪fillna(df['product_all_risks'].value_counts().idxmax())
    df['annual_price_third_party'] = df['annual_price_third_party'].
↪fillna(df['annual_price_third_party'].value_counts().idxmax())
    df['annual_price_intermediate'] = df['annual_price_intermediate'].
↪fillna(df['annual_price_intermediate'].value_counts().idxmax())
    df['annual_price_all_risks'] = df['annual_price_all_risks'].
↪fillna(df['annual_price_all_risks'].value_counts().idxmax())

    # Replacing missing values by 'None'
    df['chosen_formula'] = df['chosen_formula'].fillna('None')
    df['chosen_product'] = df['chosen_product'].fillna('None')
```

```python
    # Replacing missing values by most frequent
    df['vehicle_class'] = df['vehicle_class'].fillna(df['vehicle_class'].
 ↪value_counts().idxmax())
    df['vehicle_group'] = df['vehicle_group'].fillna(df['vehicle_group'].
 ↪value_counts().idxmax())

    # Categorical encoding
    df_dummies = pd.get_dummies(df, drop_first=True)

    return df_dummies
```

[25]:
```python
X_quotes = clean_preprocess(X_quotes)
```

[26]:
```python
X_quotes_train, X_quotes_test, y_quotes_train, y_quotes_test = 
 ↪train_test_split(X_quotes, y_quotes,
                                                                                
 ↪train_size=0.7, test_size=0.3,
                                                                                
 ↪random_state=0)
```

3.0.2 Logistic regression

https://www.kaggle.com/code/ashydv/lead-scoring-logistic-regression

[27]:
```python
lr_predictor = LogisticRegression(random_state=0, class_weight='balanced')

lr_predictor = lr_predictor.fit(X_quotes_train, y_quotes_train)
```

[28]:
```python
predict_evaluate(lr_predictor, X_quotes_train, y_quotes_train, X_quotes_test, 
 ↪y_quotes_test)
```

```
Predictor train accuracy: 0.815
Predictor test accuracy: 0.786
Predictor f1 score: 0.381
[[262  72]
 [  6  24]]
              precision    recall  f1-score   support

           0       0.98      0.78      0.87       334
           1       0.25      0.80      0.38        30

    accuracy                           0.79       364
   macro avg       0.61      0.79      0.63       364
weighted avg       0.92      0.79      0.83       364
```

3.0.3 Random forest

https://link.medium.com/0HeoU8Qslsb

[29]:
```
# Random Forest
rf_predictor = RandomForestClassifier(random_state=0, class_weight='balanced')

rf_predictor = rf_predictor.fit(X_quotes_train, y_quotes_train)
```

[30]:
```
predict_evaluate(rf_predictor, X_quotes_train, y_quotes_train, X_quotes_test,␣
↪y_quotes_test)
```

```
Predictor train accuracy: 1.000
Predictor test accuracy: 0.953
Predictor f1 score: 0.622
[[333   1]
 [ 16  14]]
              precision    recall  f1-score   support

           0       0.95      1.00      0.98       334
           1       0.93      0.47      0.62        30

    accuracy                           0.95       364
   macro avg       0.94      0.73      0.80       364
weighted avg       0.95      0.95      0.95       364
```

3.0.4 Logistic Regression v2.0 : Using Pipelines

[31]:
```
X_quotes = quotes[quotes_categorical_cols]
y_quotes = quotes[quotes_target_col]
y_quotes = np.where(y_quotes==False, 0, 1)
```

[32]:
```
X_quotes_train, X_quotes_test, y_quotes_train, y_quotes_test =␣
↪train_test_split(X_quotes, y_quotes,                                          ␣
↪train_size=0.7, test_size=0.3,                                                ␣
↪random_state=0)
```

[33]:
```
imputer = SimpleImputer(strategy="most_frequent")
categorical_encoder = OneHotEncoder(handle_unknown='ignore')

categorical_pipeline = Pipeline(
    [("imputer", imputer), ("encoder", categorical_encoder)]
)

preprocess_pipeline = ColumnTransformer(transformers=[
```

```
    ("category", categorical_pipeline, quotes_categorical_cols)
])
```

[34]:
```
lr_pipeline = Pipeline(
    [
        ("preprocess", preprocess_pipeline),
        ("classifier", LogisticRegression(random_state=0,␣
↪class_weight='balanced')),
    ]
)
lr_pipeline = lr_pipeline.fit(X_quotes_train, y_quotes_train)
```

```
C:\Work\Anaconda\lib\site-packages\sklearn\linear_model\_logistic.py:762:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[35]:
```
predict_evaluate(lr_pipeline, X_quotes_train, y_quotes_train, X_quotes_test,␣
↪y_quotes_test)
```

```
Predictor train accuracy: 0.810
Predictor test accuracy: 0.791
Predictor f1 score: 0.377
[[265  69]
 [  7  23]]
              precision    recall  f1-score   support

           0       0.97      0.79      0.87       334
           1       0.25      0.77      0.38        30

    accuracy                           0.79       364
   macro avg       0.61      0.78      0.63       364
weighted avg       0.91      0.79      0.83       364
```

3.0.5 Random Forest v2.0 : Using Pipelines, GridSearch and feature importance

[36]:
```
imputer = SimpleImputer(strategy="most_frequent")
categorical_encoder = OneHotEncoder(handle_unknown='ignore')

categorical_pipeline = Pipeline(
    [("imputer", imputer), ("encoder", categorical_encoder)]
```

```
)

preprocess_pipeline = ColumnTransformer(transformers=[
    ("category", categorical_pipeline, quotes_categorical_cols)
])
```

[37]:
```
rf_pipeline = Pipeline(
    [
        ("preprocess", preprocess_pipeline),
        ("classifier", RandomForestClassifier(random_state=0,␣
↪class_weight='balanced')),
    ]
)
rf_pipeline = rf_pipeline.fit(X_quotes_train, y_quotes_train)
```

[38]:
```
predict_evaluate(rf_pipeline, X_quotes_train, y_quotes_train, X_quotes_test,␣
↪y_quotes_test)
```

```
Predictor train accuracy: 1.000
Predictor test accuracy: 0.956
Predictor f1 score: 0.636
[[334   0]
 [ 16  14]]
              precision    recall  f1-score   support

           0       0.95      1.00      0.98       334
           1       1.00      0.47      0.64        30

    accuracy                           0.96       364
   macro avg       0.98      0.73      0.81       364
weighted avg       0.96      0.96      0.95       364
```

[39]:
```
rf_pipeline.get_params().keys()
```

[39]:
```
dict_keys(['memory', 'steps', 'verbose', 'preprocess', 'classifier',
'preprocess__n_jobs', 'preprocess__remainder', 'preprocess__sparse_threshold',
'preprocess__transformer_weights', 'preprocess__transformers',
'preprocess__verbose', 'preprocess__category', 'preprocess__category__memory',
'preprocess__category__steps', 'preprocess__category__verbose',
'preprocess__category__imputer', 'preprocess__category__encoder',
'preprocess__category__imputer__add_indicator',
'preprocess__category__imputer__copy',
'preprocess__category__imputer__fill_value',
'preprocess__category__imputer__missing_values',
'preprocess__category__imputer__strategy',
'preprocess__category__imputer__verbose',
'preprocess__category__encoder__categories',
```

```
'preprocess__category__encoder__drop', 'preprocess__category__encoder__dtype',
'preprocess__category__encoder__handle_unknown',
'preprocess__category__encoder__sparse', 'classifier__bootstrap',
'classifier__ccp_alpha', 'classifier__class_weight', 'classifier__criterion',
'classifier__max_depth', 'classifier__max_features',
'classifier__max_leaf_nodes', 'classifier__max_samples',
'classifier__min_impurity_decrease', 'classifier__min_impurity_split',
'classifier__min_samples_leaf', 'classifier__min_samples_split',
'classifier__min_weight_fraction_leaf', 'classifier__n_estimators',
'classifier__n_jobs', 'classifier__oob_score', 'classifier__random_state',
'classifier__verbose', 'classifier__warm_start'])
```

[40]:
```
rf_param_grid = {
    'classifier__n_estimators': [25, 50, 100],
    'classifier__max_depth': [4, 5, 6, 7],
    'classifier__min_samples_split': [2, 3, 4]
}
```

[41]:
```
rf_pipeline_gridsearch = GridSearchCV(estimator=rf_pipeline,␣
 ↪param_grid=rf_param_grid, cv=5)
rf_pipeline_gridsearch = rf_pipeline_gridsearch.fit(X_quotes_train,␣
 ↪y_quotes_train)
```

[42]:
```
rf_pipeline_gridsearch.best_params_
```

[42]:
```
{'classifier__max_depth': 7,
 'classifier__min_samples_split': 4,
 'classifier__n_estimators': 100}
```

[43]:
```
rf_pipeline_best = Pipeline(
    [
        ("preprocess", preprocess_pipeline),
        ("classifier", RandomForestClassifier(random_state=0,␣
 ↪class_weight='balanced',
                                              max_depth=rf_pipeline_gridsearch.
 ↪best_params_['classifier__max_depth'],
                                                                             ␣
 ↪min_samples_split=rf_pipeline_gridsearch.
 ↪best_params_['classifier__min_samples_split'],
                                                                             ␣
 ↪n_estimators=rf_pipeline_gridsearch.
 ↪best_params_['classifier__n_estimators']))
    ]
)
rf_pipeline_best = rf_pipeline_best.fit(X_quotes_train, y_quotes_train)
```

[44]:
```
predict_evaluate(rf_pipeline_best, X_quotes_train, y_quotes_train,␣
↪X_quotes_test, y_quotes_test)
```

```
Predictor train accuracy: 0.889
Predictor test accuracy: 0.865
Predictor f1 score: 0.462
[[294  40]
 [  9  21]]
              precision    recall  f1-score   support

           0       0.97      0.88      0.92       334
           1       0.34      0.70      0.46        30

    accuracy                           0.87       364
   macro avg       0.66      0.79      0.69       364
weighted avg       0.92      0.87      0.89       364
```

Score repartition

[45]:
```
y_pred = rf_pipeline_best.predict_proba(X_quotes_test)
```

[46]:
```
df_pred = pd.DataFrame(y_pred, columns = ['neg_score','pos_score'])
```

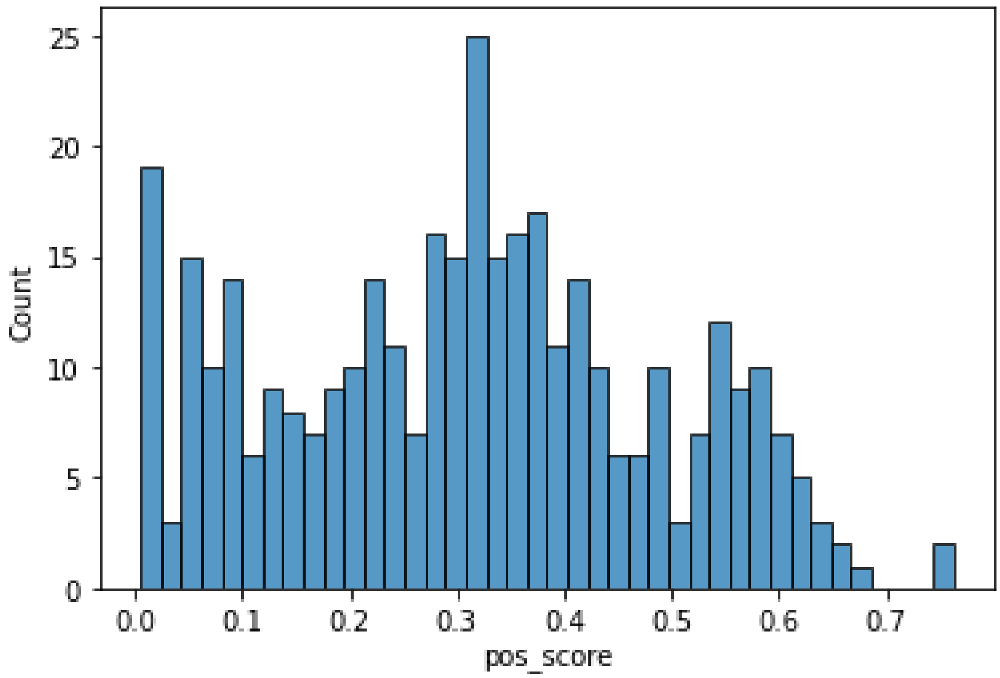
[47]:
```
df_pred.head()
```

[47]:

	neg_score	pos_score
0	0.988412	0.011588
1	0.570049	0.429951
2	0.637114	0.362886
3	0.821664	0.178336
4	0.703515	0.296485

[48]:
```
sns.histplot(data=df_pred, x="pos_score", bins=40)
```

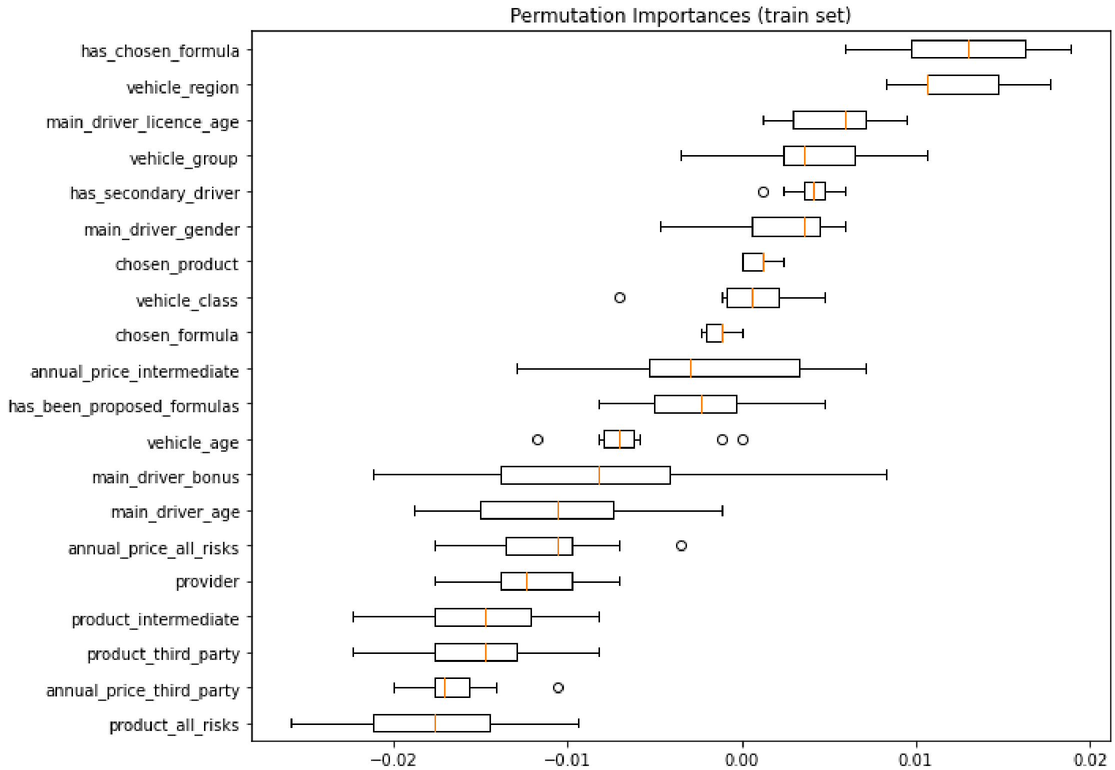
[48]:
```
<AxesSubplot:xlabel='pos_score', ylabel='Count'>
```



Feature importance

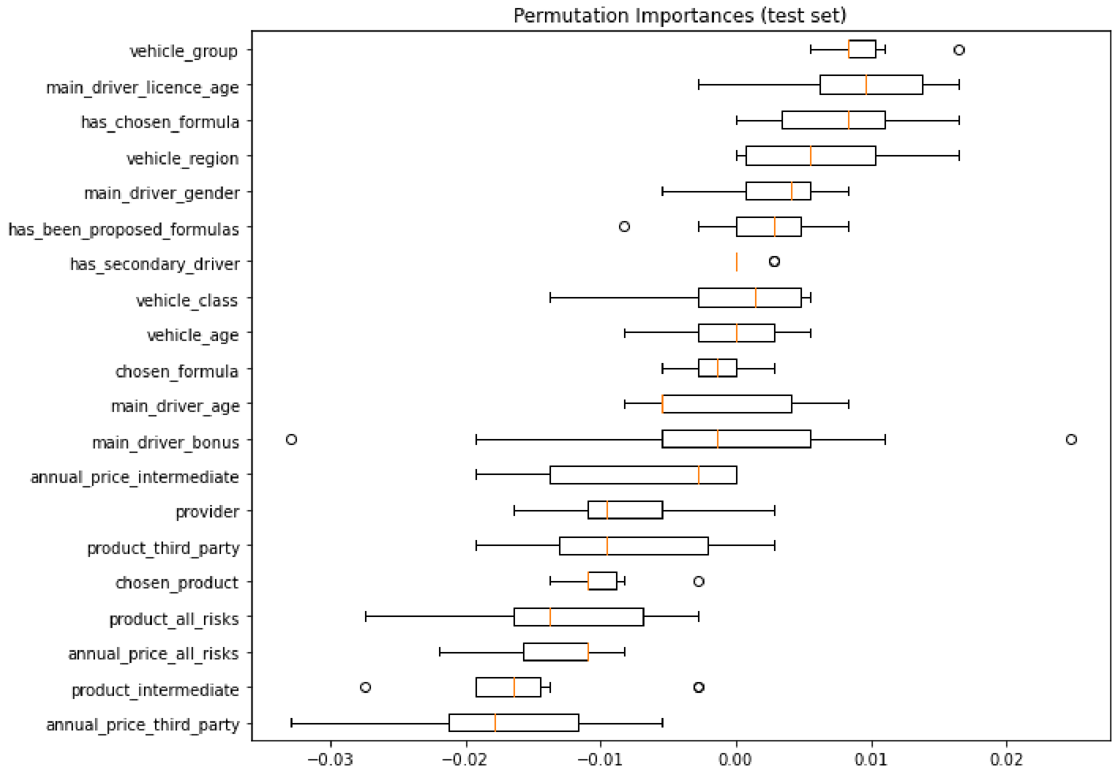
[49]:
```
result = permutation_importance(rf_pipeline_best, X_quotes_train,␣
↪y_quotes_train, n_repeats=10,
                                random_state=0, n_jobs=2)
sorted_idx = result.importances_mean.argsort()

fig, ax = plt.subplots(figsize=FIGSIZE)
ax.boxplot(result.importances[sorted_idx].T,
           vert=False, labels=X_quotes_train.columns[sorted_idx])
ax.set_title("Permutation Importances (train set)")
fig.tight_layout()
plt.show()
```



[50]:
```
result = permutation_importance(rf_pipeline_best, X_quotes_test, y_quotes_test,␣
↪n_repeats=10,
                                random_state=0, n_jobs=2)
sorted_idx = result.importances_mean.argsort()

fig, ax = plt.subplots(figsize=FIGSIZE)
ax.boxplot(result.importances[sorted_idx].T,
           vert=False, labels=X_quotes_test.columns[sorted_idx])
ax.set_title("Permutation Importances (test set)")
fig.tight_layout()
plt.show()
```



[51]:
```
train_fi_list = X_quotes_train.columns[sorted_idx]
test_fi_list = X_quotes_test.columns[sorted_idx]
```

[52]:
```
test_fi_list
```

[52]:
```
Index(['annual_price_third_party', 'product_intermediate',
       'annual_price_all_risks', 'product_all_risks', 'chosen_product',
       'product_third_party', 'provider', 'annual_price_intermediate',
       'main_driver_bonus', 'main_driver_age', 'chosen_formula', 'vehicle_age',
       'vehicle_class', 'has_secondary_driver', 'has_been_proposed_formulas',
       'main_driver_gender', 'vehicle_region', 'has_chosen_formula',
       'main_driver_licence_age', 'vehicle_group'],
      dtype='object')
```

[53]:
```
# FIXME : graph to show how features go up and down in ranking
```

3.0.6 Support Vector Machine

[54]:
```
svm_pipeline = Pipeline(
    [
        ("preprocess", preprocess_pipeline),
        ("classifier", svm.SVC(class_weight='balanced')),
```

```
    ]
)
svm_pipeline = svm_pipeline.fit(X_quotes_train, y_quotes_train)
```

[55]:
```
predict_evaluate(svm_pipeline, X_quotes_train, y_quotes_train, X_quotes_test,␣
 ↪y_quotes_test)
```

```
Predictor train accuracy: 0.894
Predictor test accuracy: 0.852
Predictor f1 score: 0.438
[[289  45]
 [  9  21]]
              precision    recall  f1-score   support

           0       0.97      0.87      0.91       334
           1       0.32      0.70      0.44        30

    accuracy                           0.85       364
   macro avg       0.64      0.78      0.68       364
weighted avg       0.92      0.85      0.88       364
```

3.0.7 Result recap

[56]:
```
def compare_model_perf(dict_models, X_quotes_train, y_quotes_train,␣
 ↪X_quotes_test, y_quotes_test):
    """Compare model performances."""
    l_main = []
    for key, model in dict_models.items():
        (train_acc, test_acc, f1_score) = predict_evaluate(model,␣
 ↪X_quotes_train, y_quotes_train,
                                                            X_quotes_test,␣
 ↪y_quotes_test, response=True)
        l_main.append([key, train_acc, test_acc, f1_score])
    return l_main
```

[57]:
```
scores = compare_model_perf({"logistic_regression": lr_pipeline,
                    "random_forest": rf_pipeline_best,
                    "svm": svm_pipeline},
                   X_quotes_train, y_quotes_train, X_quotes_test, y_quotes_test)
```

[58]:
```
df_scores = pd.DataFrame(scores, columns = ['model_name', 'train_acc',␣
 ↪'test_acc', 'f1_score'])
```

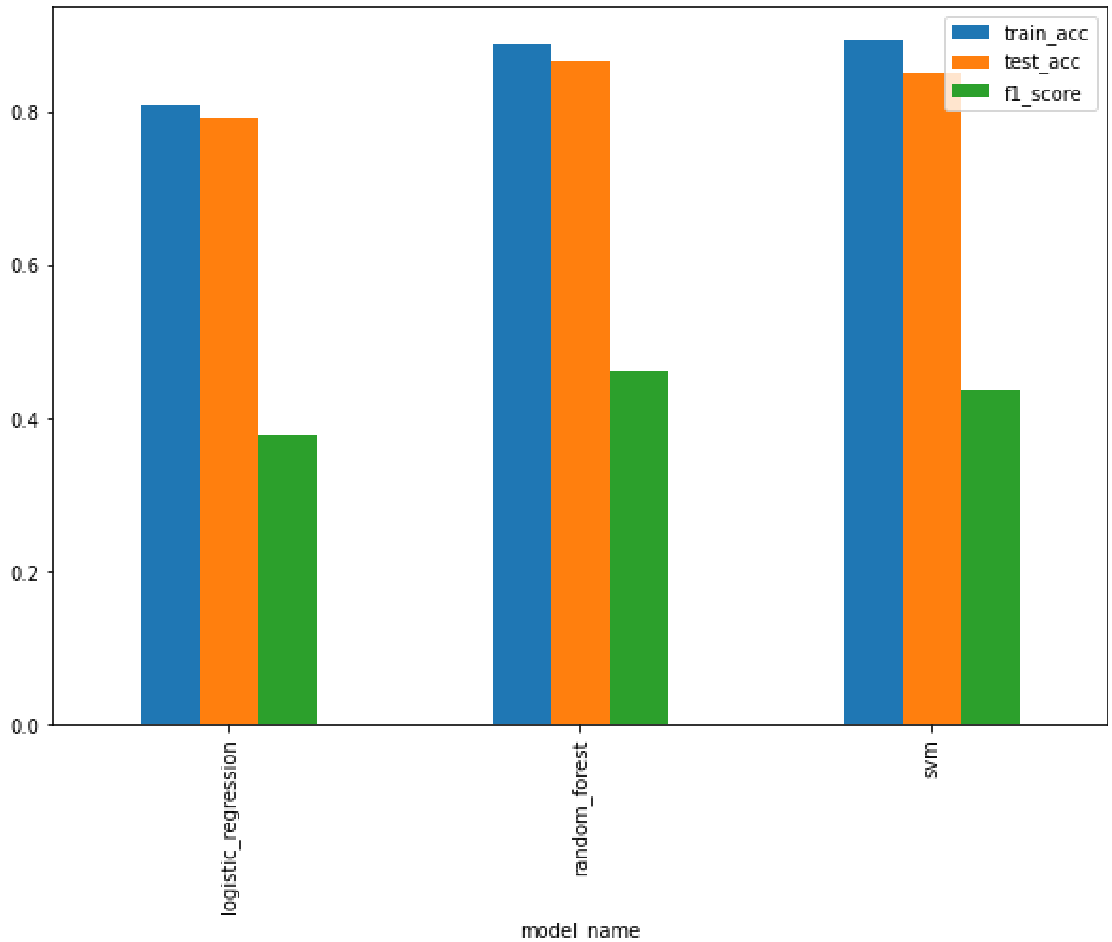
[59]:
```
df_scores
```

[59]:

	model_name	train_acc	test_acc	f1_score
0	logistic_regression	0.810142	0.791209	0.377049
1	random_forest	0.889151	0.865385	0.461538
2	svm	0.893868	0.851648	0.437500

[60]:
```
df_scores.plot(x="model_name", y=["train_acc", "test_acc", "f1_score"],␣
↪kind="bar", figsize=FIGSIZE)
```

[60]: <AxesSubplot:xlabel='model_name'>



3.0.8 PKL export best model

[61]:
```
filename = 'rf_pipeline.pkl'
pickle.dump(rf_pipeline, open(filename, 'wb'))
```

[ ]:
```
```

4 3. Données additionnelles

- **Campagnes Marketing :** Avoir les data des clics / open rate
- **Historiques des appels téléphoniques :** Avoir les données des appels pour voir la corrélation entre les relances téléphoniques et la conversion en client
- **Browsing logs :** Avoir le nombre de fois qu'ils sont venus sur le site + la durée des sessions

5 4. Les applications chez Ornikar

- **Campagnes marketing :** Target les lead avec le score le plus haut avec des campagnes marketing pour réduire la pression commerciale et optimiser les campagnes.
- **Customer Care :** Outils Customer Care qui demandent le score du lead en temps réel pour une meilleure compréhension du lead.
- **Sales/CC :** Relances téléphoniques priorisées en fonction du score du lead.

6 (5. Les pistes d'améliorations / next steps)

- Améliorer le feature engineering :
  - Ajouter le nombre de devis réalisés par lead
  - Regrouper des valeurs similaires sur des features avec de nombreuses valeurs
  - Passer les features initallement numériques en numérique : main_driver_licence_age ; main_driver_bonus
  - Prendre plus de temps pour étudier chaque feature
- Ajouter les données de mixpanel.csv pour enrichir les données
- Mieux étudier les résultats des modèles pour mieux les évaluer :
  - Faire intervenir d'autres métriques
  - Savoir qu'est-ce qui est le plus dommageable : avoir plus de Faux Positif ou de Faux Négatif ? Instinctivement je dirais que avoir des Faux Positif mois grave que Faux Négatif car peu de données.
- Améliorer la mise en production :
  - Utiliser un modèle registry : dvc
  - Investiguer pour améliorer les performances de l'API
  - Ajouter un path à l'API qui permet d'avoir accès aux scores précalculés sur BigQuery

long_quotes.csv : Table de production qui contient des informations relatives aux devis d'assurance auto entrants

long_quote_id : ID du devis

lead_id : ID du lead

country_code : Code pays

first_utm_source : Première source UTM connue pour ce lead

last_utm_source : Dernière source UTM connue pour ce lead, avant le devis

has_been_proposed_formulas : Si Ornikar a proposé d'assurer le lead

has_chosen_formula : Si le lead a cliqué sur une formule proposée

has_subscribed_online : Si le lead a souscrit un contrat en ligne submitted_at : Timestamp de complétion du devis

effective_start_date : Date de début souhaitée du contrat

rbs_result : Résultat du test psychologique qui est proposé aux jeunes conducteurs

provider : Fournisseur de contrat d'assurance

product_third_party : Produit au tiers proposé

product_intermediate : Produit intermédiaire proposé

product_all_risks : Produit tous risques proposé

annual_price_third_party : niveau de prix au tiers proposé

annual_price_intermediate : niveau de prix intermédiaire proposé

annual_price_all_risks : niveau de prix tous risques proposé

chosen_formula : Formule sur laquelle le lead a cliqué

chosen_product : Produit correspondant à la formule sur laquelle le lead a cliqué

policy_subscribed_at : Timestamp de souscription du contrat en ligne

contract_id : ID du contrat souscrit en ligne

payment_frequency : Fréquence de paiement choisie

main_driver_age : Catégorie d'âge du lead

main_driver_gender : Genre du lead

main_driver_licence_age : Catégorie d'ancienneté du permis du lead

main_driver_bonus : Catégorie de bonus/malus du lead

vehicle_age : Catégorie d'ancienneté du véhicule du lead

vehicle_class : Catégorie de classe du véhicule du lead

vehicle_group : Catégorie de groupe du véhicule du lead

vehicle_region : Région de parking du véhicule du lead

has_secondary_driver : Si le devis inclut un conducteur secondaire

has_subscribed : Si le lead a souscrit un contrat (en ligne ou via le service clients)

mixpanel.csv : Table issue du tracking qui contient des événements du parcours de souscription pour l'assurance auto

time : Timestamp de réception de l'événement

page_view : URL depuis laquelle l'événement a été reçu

mp_os : Système d'exploitation du lead

mp_browser : Navigateur du lead

utm_source : Source de trafic du lead

insurance_subscription : Données spécifiques au parcours de souscription assurance long_quote_id lead_id category_quoted_tiers : si le lead vient de la landing page pour jeunes conducteur ou non broker_name : équivalent du champ provider_name lead_quote_status : équivalent du champ has_been_proposed_formulas nogo_reason : raison pour laquelle lead_quote_status = NoGo vehicle_search_method : méthode choisie pour le début du devis (soit en rentrant directement la plaque d'immatriculation, soit en cliquant sur la marque de son véhicule) product_name : si le lead vient de la landing page pour jeunes conducteur ou non product_type : équivalent de chosen_formula warranties : non utilisé

mp_event_name : Nom de l'événement, différentes possibilités dans l'ordre : Insurance - Initiate Insurance Long Quote : début de devis depuis https://www.ornikar.com/assurance-auto Insurance - Complete Insurance Long Quote : fin de devis, cet événement est envoyé au moment où l'on ajoute une ligne dans la table long_quotes Insurance - Customize Insurance Contract : choix d'une formule parmi celles proposées Insurance - New Subscription Online : souscription d'un contrat en ligne

```
[ ]:
```