General information

In this kernel I work with IEEE Fraud Detection competition.

EEE-CIS works across a variety of AI and machine learning areas, including deep neural networks, fuzzy systems, evolutionary computation, and swarm intelligence. Today they’re partnering with the world’s leading payment service company, Vesta Corporation, seeking the best solutions for fraud prevention industry, and now you are invited to join the challenge.

We have a binary classification problem with a heavy imbalance which is an inherent property of such problems. At first I'll explore the data and try to find valuable insights, maybe I'll do some feature engineering and then it wil be time to build models.

Work in progress

In [1]:
```
!pip install -U vega_datasets notebook vega
```

```
Collecting vega_datasets
  Downloading https://files.pythonhosted.org/packages/0a/53/00c0d891e2da61442745aa5f6677e93b68ea247b49ed70a7da1dd764760f/vega_datasets-0.7.0-py2.py3-none-any.whl (209kB)
     |████████████████████████████████| 215kB 3.4MB/s
Collecting notebook
  Downloading https://files.pythonhosted.org/packages/f3/a1/1e07cedcb554408fefe4a7d32b2a041c86517167aec6ca8251c808ef6c1e/notebook-6.0.1-py3-none-any.whl (9.0MB)
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Collecting vega
  Downloading https://files.pythonhosted.org/packages/2b/cf/72b9200c09464ca28e38f1dec85d1773858fd641fae3a97c64d1fc495b27/vega-2.6.0-py3-none-any.whl (2.2MB)
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Requirement already satisfied, skipping upgrade: pandas in /opt/conda/lib/python3.6/site-packages (from vega_datasets) (0.25.0)
Requirement already satisfied, skipping upgrade: terminado>=0.8.1 in /opt/conda/lib/python3.6/site-packages (from notebook) (0.8.2)
Requirement already satisfied, skipping upgrade: prometheus-client in /opt/conda/lib/python3.6/site-packages (from notebook) (0.7.1)
Requirement already satisfied, skipping upgrade: ipykernel in /opt/conda/lib/python3.6/site-packages (from notebook) (5.1.2)
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Requirement already satisfied, skipping upgrade: ipython-genutils in /opt/conda/lib/python3.6/site-packages (from notebook) (0.2.0)
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Requirement already satisfied, skipping upgrade: traitlets>=4.2.1 in /opt/conda/lib/python3.6/site-packages (from notebook) (4.3.2)
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Requirement already satisfied, skipping upgrade: jupyter-core>=4.4.0 in /opt/conda/lib/python3.6/site-packages (from notebook) (4.5.0)
Requirement already satisfied, skipping upgrade: pytz>=2017.2 in /opt/conda/lib/python3.6/site-packages (from pandas->vega_datasets) (2019.2)
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Requirement already satisfied, skipping upgrade: numpy>=1.13.3 in /opt/conda/lib/python3.6/site-packages (from pandas->vega_datasets) (1.17.0)
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Requirement already satisfied, skipping upgrade: prompt-toolkit<2.1.0,>=2.0.0 in /opt/conda/lib/python3.6/site-packages (from ipython>=5.0.0->ipykernel->notebook) (2.0.9)
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Requirement already satisfied, skipping upgrade: setuptools>=18.5 in /opt/conda/lib/python3.6/site-packages (from ipython>=5.0.0->ipykernel->notebook) (41.0.1)
Requirement already satisfied, skipping upgrade: pickleshare in /opt/conda/lib/python3.6/site-packages (from ipython>=5.0.0->ipykernel->notebook) (0.7.5)
Requirement already satisfied, skipping upgrade: backcall in /opt/conda/lib/python3.6/site-packages (from ipython>=5.0.0->ipykernel->notebook) (0.1.0)
Requirement already satisfied, skipping upgrade: pyrsistent>=0.14.0 in /opt/conda/lib/python3.6/site-packages (from jsonschema!=2.5.0,>=2.4->nbformat->notebook) (0.14.11)
Requirement already satisfied, skipping upgrade: attrs>=17.4.0 in /opt/conda/lib/python3.6/site-packages (from jsonschema!=2.5.0,>=2.4->nbformat->notebook) (19.1.0)
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Requirement already satisfied, skipping upgrade: wcwidth in /opt/conda/lib/python3.6/site-packages (from prompt-toolkit<2.1.0,>=2.0.0->ipython>=5.0.0->ipykernel->notebook) (0.1.7)
Requirement already satisfied, skipping upgrade: ptyprocess>=0.5 in /opt/conda/lib/python3.6/site-packages (from pexpect; sys_platform != "win32"->ipython>=5.0.0->ipykernel->notebook) (0.6.0)
Requirement already satisfied, skipping upgrade: parso>=0.5.0 in /opt/conda/lib/python3.6/site-packages (from jedi>=0.10->ipython>=5.0.0->ipykernel->notebook) (0.5.1)
ERROR: cufflinks 0.16 has requirement plotly<4.0.0a0,>=3.0.0, but you'll have plotly 4.1.0 which is incompatible.
Installing collected packages: vega-datasets, notebook, vega
  Found existing installation: notebook 5.5.0
    Uninstalling notebook-5.5.0:
      Successfully uninstalled notebook-5.5.0
Successfully installed notebook-6.0.1 vega-2.6.0 vega-datasets-0.7.0
```

Importing libraries

In [2]:
```
import numpy as np
import pandas as pd
import os

import matplotlib.pyplot as plt
%matplotlib inline
from tqdm import tqdm_notebook
from sklearn.preprocessing import StandardScaler
from sklearn.svm import NuSVR, SVR
from sklearn.metrics import mean_absolute_error
pd.options.display.precision = 15

import lightgbm as lgb
import xgboost as xgb
import time
import datetime
from catboost import CatBoostRegressor
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import StratifiedKFold, KFold, RepeatedKFold, GroupKFold, GridSearchCV, train_test_split, TimeSeriesSplit
from sklearn import metrics
from sklearn import linear_model
import gc
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")

import eli5
import shap
from IPython.display import HTML
import json
import altair as alt

import networkx as nx
import matplotlib.pyplot as plt
%matplotlib inline

alt.renderers.enable('notebook')

%env JOBLIB_TEMP_FOLDER=/tmp
```

```
Using TensorFlow backend.
```

```
env: JOBLIB_TEMP_FOLDER=/tmp
```

Functions used in this kernel

They are in the hidden cell below.

In [3]:
```
import os
import time
import datetime
import json
import gc
from numba import jit

import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns
from tqdm import tqdm_notebook

import lightgbm as lgb
import xgboost as xgb
from catboost import CatBoostRegressor, CatBoostClassifier
from sklearn import metrics

from itertools import product

import altair as alt
from altair.vega import v5
from IPython.display import HTML

# using ideas from this kernel: https://www.kaggle.com/notslush/altair-visualization-2018-stackoverflow-survey
def prepare_altair():
    """
    Helper function to prepare altair for working.
    """

    vega_url = 'https://cdn.jsdelivr.net/npm/vega@' + v5.SCHEMA_VERSION
    vega_lib_url = 'https://cdn.jsdelivr.net/npm/vega-lib'
    vega_lite_url = 'https://cdn.jsdelivr.net/npm/vega-lite@' + alt.SCHEMA_VERSION
    vega_embed_url = 'https://cdn.jsdelivr.net/npm/vega-embed@3'
    noext = "?noext"

    paths = {
        'vega': vega_url + noext,
        'vega-lib': vega_lib_url + noext,
        'vega-lite': vega_lite_url + noext,
        'vega-embed': vega_embed_url + noext
    }

    workaround = f"""    requirejs.config({{
        baseUrl: 'https://cdn.jsdelivr.net/npm/',
        paths: {paths}
    }});
    """

    return workaround


def add_autoincrement(render_func):
    # Keep track of unique <div/> IDs
    cache = {}
    def wrapped(chart, id="vega-chart", autoincrement=True):
        if autoincrement:
            if id in cache:
                counter = 1 + cache[id]
                cache[id] = counter
            else:
                cache[id] = 0
            actual_id = id if cache[id] == 0 else id + '-' + str(cache[id])
        else:
            if id not in cache:
                cache[id] = 0
            actual_id = id
        return render_func(chart, id=actual_id)
    # Cache will stay outside and
    return wrapped


@add_autoincrement
def render(chart, id="vega-chart"):
    """
    Helper function to plot altair visualizations.
    """
    chart_str = """
    <div id="{id}"></div><script>
    require(["vega-embed"], function(vg_embed) {{
        const spec = {chart};
        vg_embed("#{id}", spec, {{defaultStyle: true}}).catch(console.warn);
        console.log("anything?");
    }});
    console.log("really...anything?");
    </script>
    """
    return HTML(
        chart_str.format(
            id=id,
            chart=json.dumps(chart) if isinstance(chart, dict) else chart.to_json(indent=None)
        )
    )


def reduce_mem_usage(df, verbose=True):
    numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
    start_mem = df.memory_usage(deep=True).sum() / 1024**2
    for col in df.columns:
        col_type = df[col].dtypes
        if col_type in numerics:
            c_min = df[col].min()
            c_max = df[col].max()
            if str(col_type)[:3] == 'int':
                if c_min > np.iinfo(np.int8).min and c_max < np.iinfo(np.int8).max:
                    df[col] = df[col].astype(np.int8)
                elif c_min > np.iinfo(np.int16).min and c_max < np.iinfo(np.int16).max:
                    df[col] = df[col].astype(np.int16)
                elif c_min > np.iinfo(np.int32).min and c_max < np.iinfo(np.int32).max:
                    df[col] = df[col].astype(np.int32)
                elif c_min > np.iinfo(np.int64).min and c_max < np.iinfo(np.int64).max:
                    df[col] = df[col].astype(np.int64)
            else:
                c_prec = df[col].apply(lambda x: np.finfo(x).precision).max()
                if c_min > np.finfo(np.float32).min and c_max < np.finfo(np.float32).max and c_prec == np.finfo(np.float32).precision:
                    df[col] = df[col].astype(np.float32)
                else:
                    df[col] = df[col].astype(np.float64)
    end_mem = df.memory_usage(deep=True).sum() / 1024**2
    if verbose: print('Mem. usage decreased to {:5.2f} Mb ({:.1f}% reduction)'.format(end_mem, 100 * (start_mem - end_mem) / start_mem))
    return df


@jit
def fast_auc(y_true, y_prob):
    """
    fast roc_auc computation: https://www.kaggle.com/c/microsoft-malware-prediction/discussion/76013
    """
    y_true = np.asarray(y_true)
    y_true = y_true[np.argsort(y_prob)]
    nfalse = 0
    auc = 0
    n = len(y_true)
    for i in range(n):
        y_i = y_true[i]
        nfalse += (1 - y_i)
        auc += y_i * nfalse
    auc /= (nfalse * (n - nfalse))
    return auc


def eval_auc(y_true, y_pred):
    """
    Fast auc eval function for lgb.
    """
    return 'auc', fast_auc(y_true, y_pred), True


def group_mean_log_mae(y_true, y_pred, types, floor=1e-9):
    """
    Fast metric computation for this competition: https://www.kaggle.com/c/champs-scalar-coupling
    Code is from this kernel: https://www.kaggle.com/uberkinder/efficient-metric
    """
    maes = (y_true-y_pred).abs().groupby(types).mean()
    return np.log(maes.map(lambda x: max(x, floor))).mean()


def train_model_regression(X, X_test, y, params, folds=None, model_type='lgb', eval_metric='mae', columns=None, plot_feature_importance=False, model=None,
                               verbose=10000, early_stopping_rounds=200, n_estimators=50000, splits=None, n_folds=3):
    """
    A function to train a variety of regression models.
    Returns dictionary with oof predictions, test predictions, scores and, if necessary, feature importances.

    :params: X - training data, can be pd.DataFrame or np.ndarray (after normalizing)
    :params: X_test - test data, can be pd.DataFrame or np.ndarray (after normalizing)
    :params: y - target
    :params: folds - folds to split data
    :params: model_type - type of model to use
    :params: eval_metric - metric to use
    :params: columns - columns to use. If None - use all columns
    :params: plot_feature_importance - whether to plot feature importance of LGB
    :params: model - sklearn model, works only for "sklearn" model type

    """
    columns = X.columns if columns is None else columns
    X_test = X_test[columns]
    splits = folds.split(X) if splits is None else splits
    n_splits = folds.n_splits if splits is None else n_folds

    # to set up scoring parameters
    metrics_dict = {'mae': {'lgb_metric_name': 'mae',
                        'catboost_metric_name': 'MAE',
                        'sklearn_scoring_function': metrics.mean_absolute_error},
                    'group_mae': {'lgb_metric_name': 'mae',
                        'catboost_metric_name': 'MAE',
                        'scoring_function': group_mean_log_mae},
                    'mse': {'lgb_metric_name': 'mse',
                        'catboost_metric_name': 'MSE',
                        'sklearn_scoring_function': metrics.mean_squared_error}
                    }


    result_dict = {}

    # out-of-fold predictions on train data
    oof = np.zeros(len(X))

    # averaged predictions on train data
    prediction = np.zeros(len(X_test))

    # list of scores on folds
    scores = []
    feature_importance = pd.DataFrame()

    # split and train on folds
    for fold_n, (train_index, valid_index) in enumerate(splits):
        if verbose:
            print(f'Fold {fold_n + 1} started at {time.ctime()}')
        if type(X) == np.ndarray:
            X_train, X_valid = X[columns][train_index], X[columns][valid_index]
            y_train, y_valid = y[train_index], y[valid_index]
        else:
            X_train, X_valid = X[columns].iloc[train_index], X[columns].iloc[valid_index]
            y_train, y_valid = y.iloc[train_index], y.iloc[valid_index]

        if model_type == 'lgb':
            model = lgb.LGBMRegressor(**params, n_estimators = n_estimators, n_jobs = -1)
            model.fit(X_train, y_train,
                    eval_set=[(X_train, y_train), (X_valid, y_valid)], eval_metric=metrics_dict[eval_metric]['lgb_metric_name'],
                    verbose=verbose, early_stopping_rounds=early_stopping_rounds)

            y_pred_valid = model.predict(X_valid)
            y_pred = model.predict(X_test, num_iteration=model.best_iteration_)

        if model_type == 'xgb':
            train_data = xgb.DMatrix(data=X_train, label=y_train, feature_names=X.columns)
            valid_data = xgb.DMatrix(data=X_valid, label=y_valid, feature_names=X.columns)

            watchlist = [(train_data, 'train'), (valid_data, 'valid_data')]
            model = xgb.train(dtrain=train_data, num_boost_round=20000, evals=watchlist, early_stopping_rounds=200, verbose_eval=verbose, params=params)
            y_pred_valid = model.predict(xgb.DMatrix(X_valid, feature_names=X.columns), ntree_limit=model.best_ntree_limit)
            y_pred = model.predict(xgb.DMatrix(X_test, feature_names=X.columns), ntree_limit=model.best_ntree_limit)

        if model_type == 'sklearn':
            model = model
            model.fit(X_train, y_train)

            y_pred_valid = model.predict(X_valid).reshape(-1,)
            score = metrics_dict[eval_metric]['sklearn_scoring_function'](y_valid, y_pred_valid)
            print(f'Fold {fold_n}. {eval_metric}: {score:.4f}.')
            print('')

            y_pred = model.predict(X_test).reshape(-1,)

        if model_type == 'cat':
            model = CatBoostRegressor(iterations=20000,  eval_metric=metrics_dict[eval_metric]['catboost_metric_name'], **params,
                                      loss_function=metrics_dict[eval_metric]['catboost_metric_name'])
            model.fit(X_train, y_train, eval_set=(X_valid, y_valid), cat_features=[], use_best_model=True, verbose=False)

            y_pred_valid = model.predict(X_valid)
            y_pred = model.predict(X_test)

        oof[valid_index] = y_pred_valid.reshape(-1,)
        if eval_metric != 'group_mae':
            scores.append(metrics_dict[eval_metric]['sklearn_scoring_function'](y_valid, y_pred_valid))
        else:
            scores.append(metrics_dict[eval_metric]['scoring_function'](y_valid, y_pred_valid, X_valid['type']))

        prediction += y_pred

        if model_type == 'lgb' and plot_feature_importance:
            # feature importance
            fold_importance = pd.DataFrame()
            fold_importance["feature"] = columns
            fold_importance["importance"] = model.feature_importances_
            fold_importance["fold"] = fold_n + 1
            feature_importance = pd.concat([feature_importance, fold_importance], axis=0)

    prediction /= n_splits
    print('CV mean score: {0:.4f}, std: {1:.4f}.'.format(np.mean(scores), np.std(scores)))

    result_dict['oof'] = oof
    result_dict['prediction'] = prediction
    result_dict['scores'] = scores

    if model_type == 'lgb':
        if plot_feature_importance:
            feature_importance["importance"] /= n_splits
            cols = feature_importance[["feature", "importance"]].groupby("feature").mean().sort_values(
                by="importance", ascending=False)[:50].index

            best_features = feature_importance.loc[feature_importance.feature.isin(cols)]

            plt.figure(figsize=(16, 12));
            sns.barplot(x="importance", y="feature", data=best_features.sort_values(by="importance", ascending=False));
            plt.title('LGB Features (avg over folds)');

            result_dict['feature_importance'] = feature_importance

    return result_dict



def train_model_classification(X, X_test, y, params, folds, model_type='lgb', eval_metric='auc', columns=None, plot_feature_importance=False, model=None,
                               verbose=10000, early_stopping_rounds=200, n_estimators=50000, splits=None, n_folds=3, averaging='usual', n_jobs=-1):
    """
    A function to train a variety of classification models.
    Returns dictionary with oof predictions, test predictions, scores and, if necessary, feature importances.

    :params: X - training data, can be pd.DataFrame or np.ndarray (after normalizing)
    :params: X_test - test data, can be pd.DataFrame or np.ndarray (after normalizing)
    :params: y - target
    :params: folds - folds to split data
    :params: model_type - type of model to use
    :params: eval_metric - metric to use
    :params: columns - columns to use. If None - use all columns
    :params: plot_feature_importance - whether to plot feature importance of LGB
    :params: model - sklearn model, works only for "sklearn" model type

    """
    columns = X.columns if columns is None else columns
    n_splits = folds.n_splits if splits is None else n_folds
    X_test = X_test[columns]

    # to set up scoring parameters
    metrics_dict = {'auc': {'lgb_metric_name': eval_auc,
                        'catboost_metric_name': 'AUC',
                        'sklearn_scoring_function': metrics.roc_auc_score},
                    }

    result_dict = {}
    if averaging == 'usual':
        # out-of-fold predictions on train data
        oof = np.zeros((len(X), 1))

        # averaged predictions on train data
        prediction = np.zeros((len(X_test), 1))

    elif averaging == 'rank':
        # out-of-fold predictions on train data
        oof = np.zeros((len(X), 1))

        # averaged predictions on train data
        prediction = np.zeros((len(X_test), 1))


    # list of scores on folds
    scores = []
    feature_importance = pd.DataFrame()

    # split and train on folds
    for fold_n, (train_index, valid_index) in enumerate(folds.split(X)):
        print(f'Fold {fold_n + 1} started at {time.ctime()}')
        if type(X) == np.ndarray:
            X_train, X_valid = X[columns][train_index], X[columns][valid_index]
            y_train, y_valid = y[train_index], y[valid_index]
        else:
            X_train, X_valid = X[columns].iloc[train_index], X[columns].iloc[valid_index]
            y_train, y_valid = y.iloc[train_index], y.iloc[valid_index]

        if model_type == 'lgb':
            model = lgb.LGBMClassifier(**params, n_estimators=n_estimators, n_jobs = n_jobs)
            model.fit(X_train, y_train,
                    eval_set=[(X_train, y_train), (X_valid, y_valid)], eval_metric=metrics_dict[eval_metric]['lgb_metric_name'],
                    verbose=verbose, early_stopping_rounds=early_stopping_rounds)

            y_pred_valid = model.predict_proba(X_valid)[:, 1]
            y_pred = model.predict_proba(X_test, num_iteration=model.best_iteration_)[:, 1]

        if model_type == 'xgb':
            train_data = xgb.DMatrix(data=X_train, label=y_train, feature_names=X.columns)
            valid_data = xgb.DMatrix(data=X_valid, label=y_valid, feature_names=X.columns)

            watchlist = [(train_data, 'train'), (valid_data, 'valid_data')]
            model = xgb.train(dtrain=train_data, num_boost_round=n_estimators, evals=watchlist, early_stopping_rounds=early_stopping_rounds, verbose_eval=verbose, params=params)
            y_pred_valid = model.predict(xgb.DMatrix(X_valid, feature_names=X.columns), ntree_limit=model.best_ntree_limit)
            y_pred = model.predict(xgb.DMatrix(X_test, feature_names=X.columns), ntree_limit=model.best_ntree_limit)

        if model_type == 'sklearn':
            model = model
            model.fit(X_train, y_train)

            y_pred_valid = model.predict(X_valid).reshape(-1,)
            score = metrics_dict[eval_metric]['sklearn_scoring_function'](y_valid, y_pred_valid)
            print(f'Fold {fold_n}. {eval_metric}: {score:.4f}.')
            print('')

            y_pred = model.predict_proba(X_test)

        if model_type == 'cat':
            model = CatBoostClassifier(iterations=n_estimators, eval_metric=metrics_dict[eval_metric]['catboost_metric_name'], **params,
                                      loss_function=Logloss)
            model.fit(X_train, y_train, eval_set=(X_valid, y_valid), cat_features=[], use_best_model=True, verbose=False)

            y_pred_valid = model.predict(X_valid)
            y_pred = model.predict(X_test)

        if averaging == 'usual':

            oof[valid_index] = y_pred_valid.reshape(-1, 1)
            scores.append(metrics_dict[eval_metric]['sklearn_scoring_function'](y_valid, y_pred_valid))

            prediction += y_pred.reshape(-1, 1)

        elif averaging == 'rank':

            oof[valid_index] = y_pred_valid.reshape(-1, 1)
            scores.append(metrics_dict[eval_metric]['sklearn_scoring_function'](y_valid, y_pred_valid))

            prediction += pd.Series(y_pred).rank().values.reshape(-1, 1)

        if model_type == 'lgb' and plot_feature_importance:
            # feature importance
            fold_importance = pd.DataFrame()
            fold_importance["feature"] = columns
            fold_importance["importance"] = model.feature_importances_
            fold_importance["fold"] = fold_n + 1
            feature_importance = pd.concat([feature_importance, fold_importance], axis=0)

    prediction /= n_splits

    print('CV mean score: {0:.4f}, std: {1:.4f}.'.format(np.mean(scores), np.std(scores)))

    result_dict['oof'] = oof
    result_dict['prediction'] = prediction
    result_dict['scores'] = scores

    if model_type == 'lgb':
        if plot_feature_importance:
            feature_importance["importance"] /= n_splits
            cols = feature_importance[["feature", "importance"]].groupby("feature").mean().sort_values(
                by="importance", ascending=False)[:50].index

            best_features = feature_importance.loc[feature_importance.feature.isin(cols)]

            plt.figure(figsize=(16, 12));
            sns.barplot(x="importance", y="feature", data=best_features.sort_values(by="importance", ascending=False));
            plt.title('LGB Features (avg over folds)');

            result_dict['feature_importance'] = feature_importance
            result_dict['top_columns'] = cols

    return result_dict

# setting up altair
workaround = prepare_altair()
HTML("".join((
    "<script>",
    workaround,
    "</script>",
)))
```

Out[3]:

Data loading and overview

Data is separated into two datasets: information about the identity of the customer and transaction information. Not all transactions belong to identities, which are available. Maybe it would be possible to use additional transactions to generate new features.

In [4]:
```
folder_path = '../input/'
train_identity = pd.read_csv(f'{folder_path}train_identity.csv')
train_transaction = pd.read_csv(f'{folder_path}train_transaction.csv')
test_identity = pd.read_csv(f'{folder_path}test_identity.csv')
test_transaction = pd.read_csv(f'{folder_path}test_transaction.csv')
sub = pd.read_csv(f'{folder_path}sample_submission.csv')
# let's combine the data and work with the whole dataset
train = pd.merge(train_transaction, train_identity, on='TransactionID', how='left')
test = pd.merge(test_transaction, test_identity, on='TransactionID', how='left')
```

In [5]:
```
print(f'Train dataset has {train.shape[0]} rows and {train.shape[1]} columns.')
print(f'Test dataset has {test.shape[0]} rows and {test.shape[1]} columns.')
```

```
Train dataset has 590540 rows and 434 columns.
Test dataset has 506691 rows and 433 columns.
```

So we have two medium-sized datasets with a lot of columns. Train and test data have similar number of rows

In [6]:
```
train_transaction.head()
```

Out[6]:

	TransactionID	isFraud	TransactionDT	TransactionAmt	ProductCD	card1	card2	card3	card4	card5	...	V330	V331	V332	V33
0	2987000	0	86400	68.5	W	13926	NaN	150.0	discover	142.0	...	NaN	NaN	NaN	Na
1	2987001	0	86401	29.0	W	2755	404.0	150.0	mastercard	102.0	...	NaN	NaN	NaN	Na
2	2987002	0	86469	59.0	W	4663	490.0	150.0	visa	166.0	...	NaN	NaN	NaN	Na
3	2987003	0	86499	50.0	W	18132	567.0	150.0	mastercard	117.0	...	NaN	NaN	NaN	Na
4	2987004	0	86506	50.0	H	4497	514.0	150.0	mastercard	102.0	...	0.0	0.0	0.0	0

5 rows × 394 columns

In [7]:
```
train_identity.head()
```

Out[7]:

	TransactionID	id_01	id_02	id_03	id_04	id_05	id_06	id_07	id_08	id_09	...	id_31	id_32	id_33	id_34	id_35	id
0	2987004	0.0	70787.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	samsung browser 6.2	32.0	2220x1080	match_status:2	T	
1	2987008	-5.0	98945.0	NaN	NaN	0.0	-5.0	NaN	NaN	NaN	...	mobile safari 11.0	32.0	1334x750	match_status:1	T	
2	2987010	-5.0	191631.0	0.0	0.0	0.0	0.0	NaN	NaN	0.0	...	chrome 62.0	NaN	NaN	NaN	F	
3	2987011	-5.0	221832.0	NaN	NaN	0.0	-6.0	NaN	NaN	NaN	...	chrome 62.0	NaN	NaN	NaN	F	
4	2987016	0.0	7460.0	0.0	0.0	1.0	0.0	NaN	NaN	0.0	...	chrome 62.0	24.0	1280x800	match_status:2	T	

5 rows × 41 columns

In [8]:
```
del train_identity, train_transaction, test_identity, test_transaction
```

In [9]:
```
print(f'There are {train.isnull().any().sum()} columns in train dataset with missing values.')
```

```
There are 414 columns in train dataset with missing values.
```

In [10]:
```
one_value_cols = [col for col in train.columns if train[col].nunique() <= 1]
one_value_cols_test = [col for col in test.columns if test[col].nunique() <= 1]
one_value_cols == one_value_cols_test
```

Out[10]:
```
False
```

In [11]:
```
print(f'There are {len(one_value_cols)} columns in train dataset with one unique value.')
print(f'There are {len(one_value_cols_test)} columns in test dataset with one unique value.')
```

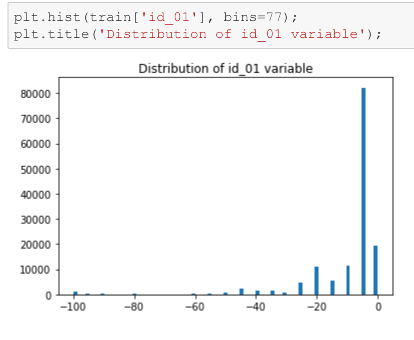
```
There are 0 columns in train dataset with one unique value.
There are 1 columns in test dataset with one unique value.
```

Most of columns have missing data, which is normal in real world. Also there are columns with one unique value (or all missing). There are a lot of continuous variables and some categorical. Let's have a closer look at them.

Data Exploration

Let's start with identity information. id_01 - id_11 are continuous variables, id_12 - id_38 are categorical and the last two columns are obviously also categorical.

In [12]:
```
plt.hist(train['id_01'], bins=77);
plt.title('Distribution of id_01 variable');
```



`id_01` has an interesting distribution: it has 77 unique non-positive values with skeweness to 0.

In [13]:
```
train['id_03'].value_counts(dropna=False, normalize=True).head()
```

Out[13]:
```
NaN    0.887689233582822
0.0    0.108211128797372
1.0    0.001461374335354
3.0    0.001131168083449
2.0    0.000712906831036
Name: id_03, dtype: float64
```

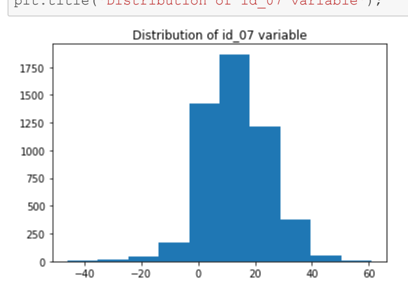
`id_03` has 88% of missing values and 98% of values are either missing or equal to 0.

In [14]:
```
train['id_11'].value_counts(dropna=False, normalize=True).head()
```

Out[14]:
```
NaN                     0.761272733430420
100.000000000000000     0.225491922647069
95.080001831054688      0.002084532800488
95.160003662109375      0.001276797507366
97.120002746582045      0.000745080773529
Name: id_11, dtype: float64
```

22% of values in `id_11` are equal to 100and 76% are missing. Quite strange.

In [15]:
```
plt.hist(train['id_07']);
plt.title('Distribution of id_07 variable');
```



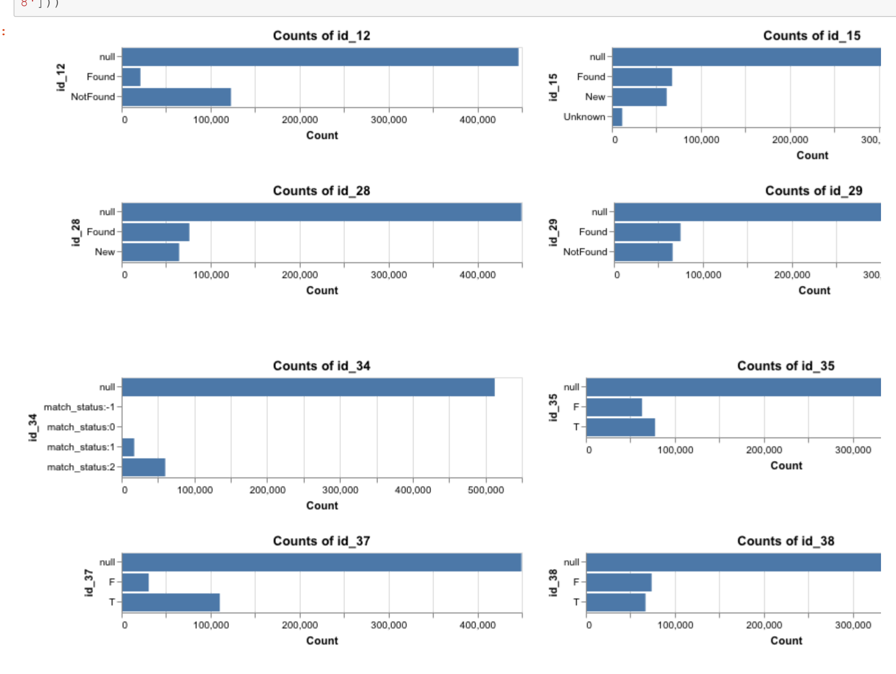
Some of features seem to be normalized. So if someone wants to normalize all variables, it would be necessary to separate such variables which seem to be already normalized.

In [16]:

```python
charts = {}
for i in ['id_12', 'id_15', 'id_16', 'id_28', 'id_29', 'id_30', 'id_31', 'id_32', 'id_33', 'id_34', 'id_35', 'id_36', 'id_37', 'id_38']:
    feature_count = train[i].value_counts(dropna=False).reset_index().rename(columns={i: 'count', 'index': i})
    chart = alt.Chart(feature_count).mark_bar().encode(
                y=alt.Y(f"{i}:N", axis=alt.Axis(title=i)),
                x=alt.X('count:Q', axis=alt.Axis(title='Count')),
                tooltip=[i, 'count']
            ).properties(title=f"Counts of {i}", width=400)
    charts[i] = chart

render((charts['id_12'] | charts['id_15'] | charts['id_16']) & (charts['id_28'] | charts['id_29'] | charts['id_32']) & (charts['id_34'] | charts['id_35'] | charts['id_36']) & (charts['id_37'] | charts['id_38']))
```

Out[16]:



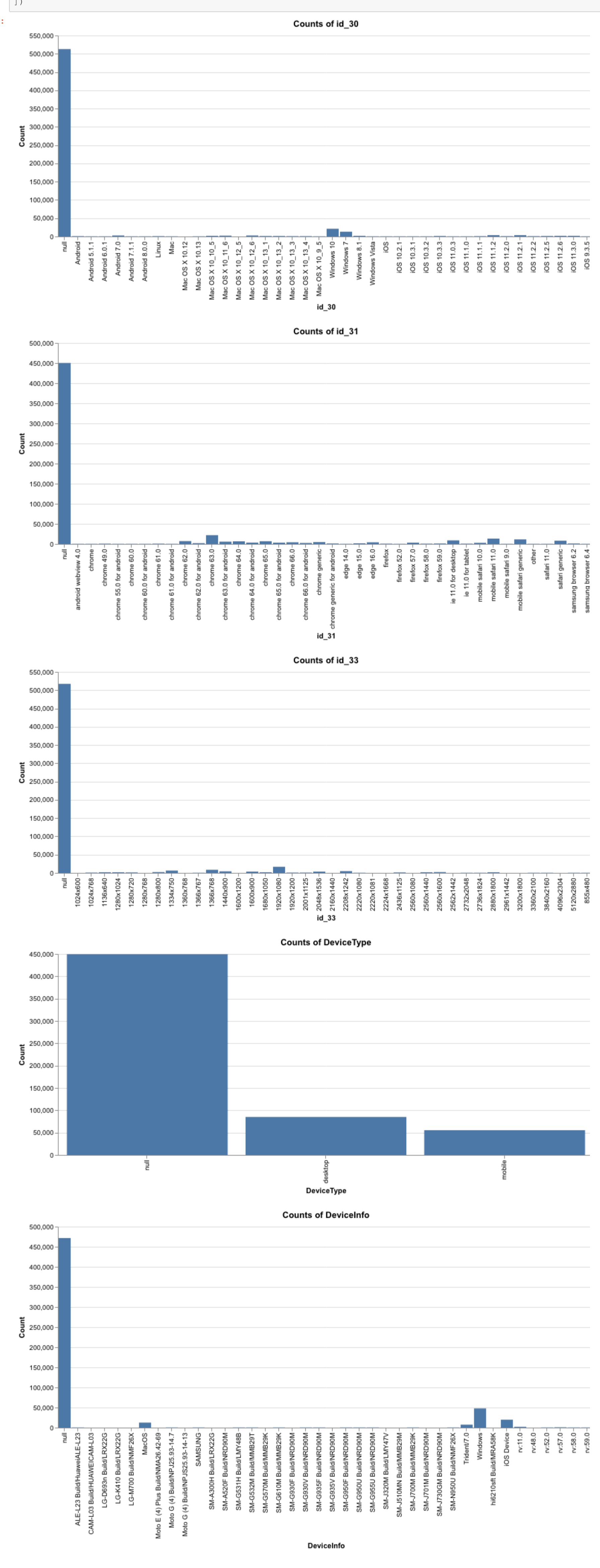
We have several features showing some kind of "found" status and several binary columns.

In [17]:

```python
charts = {}
for i in ['id_30', 'id_31', 'id_33', 'DeviceType', 'DeviceInfo']:
    feature_count = train[i].value_counts(dropna=False)[:40].reset_index().rename(columns={i: 'count', 'index': i})
    chart = alt.Chart(feature_count).mark_bar().encode(
                x=alt.X(f"{i}:N", axis=alt.Axis(title=i)),
                y=alt.Y('count:Q', axis=alt.Axis(title='Count')),
                tooltip=[i, 'count']
            ).properties(title=f"Counts of {i}", width=800)
    charts[i] = chart

render(charts['id_30'] & charts['id_31'] & charts['id_33'] & charts['DeviceType'] & charts['DeviceInfo'])
```

Out[17]:

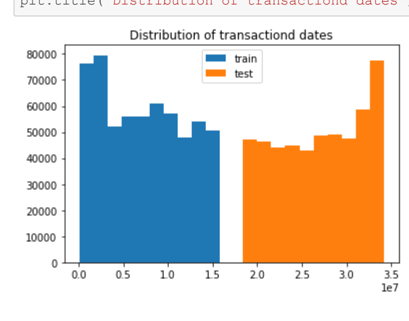


Here we can see some information about client's device. It is important to be careful here - some of info could be for old devices and may be absent from test data.

Now let's have a look at transaction data.

In [18]:

```python
plt.hist(train['TransactionDT'], label='train');
plt.hist(test['TransactionDT'], label='test');
plt.legend();
plt.title('Distribution of transactiond dates');
```



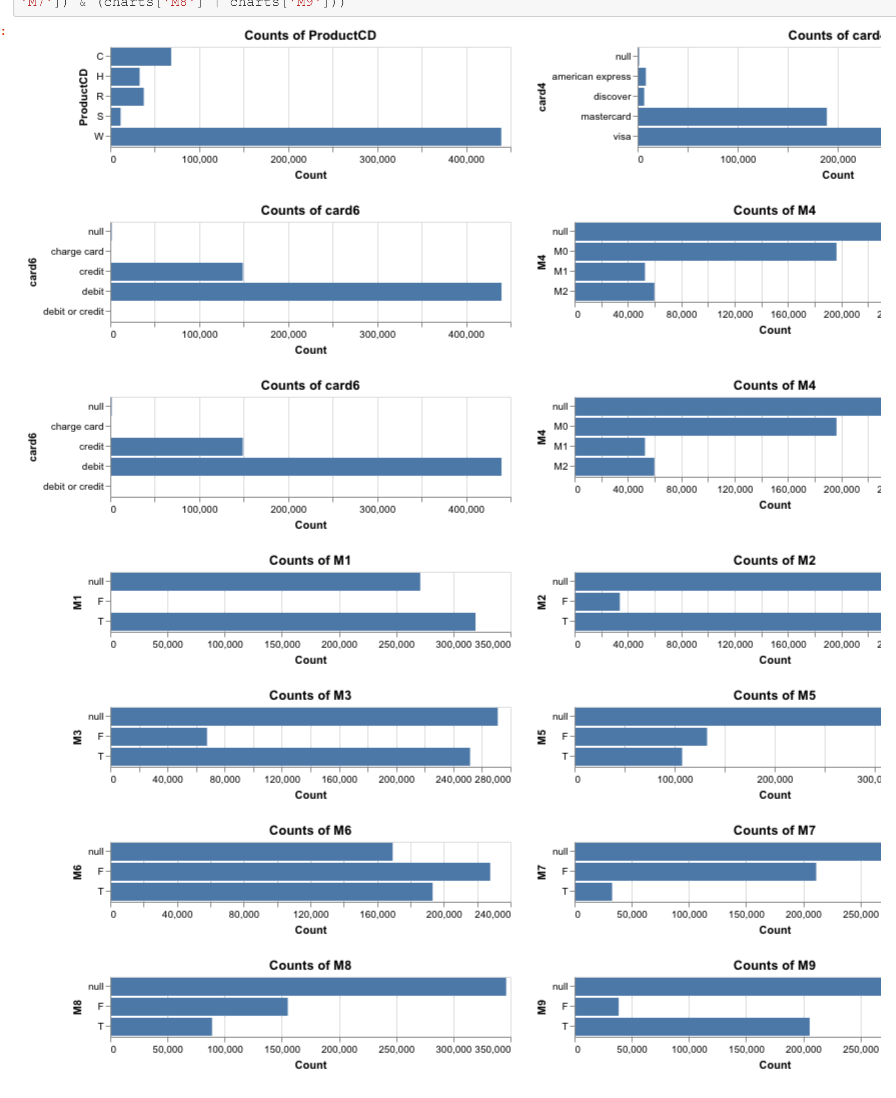
A very important idea: it seems that train and test transaction dates don't overlap, so it would be prudent to use time-based split for validation. This was already noted in abother kernel: https://www.kaggle.com/robikscube/ieee-fraud-detection-first-look-and-eda

In [19]:

```python
charts = {}
for i in ['ProductCD', 'card4', 'card6', 'M4', 'M1', 'M2', 'M3', 'M5', 'M6', 'M7', 'M8', 'M9']:
    feature_count = train[i].value_counts(dropna=False).reset_index().rename(columns={i: 'count', 'index': i})
    chart = alt.Chart(feature_count).mark_bar().encode(
                y=alt.Y(f"{i}:N", axis=alt.Axis(title=i)),
                x=alt.X('count:Q', axis=alt.Axis(title='Count')),
                tooltip=[i, 'count']
            ).properties(title=f"Counts of {i}", width=400)
    charts[i] = chart

render((charts['ProductCD'] | charts['card4']) & (charts['card6'] | charts['M4']) & (charts['card6'] | charts['M4']) & (charts['M1'] | charts['M2']) & (charts['M3'] | charts['M5']) & (charts['M6'] | charts['M7']) & (charts['M8'] | charts['M9']))
```

Out[19]:



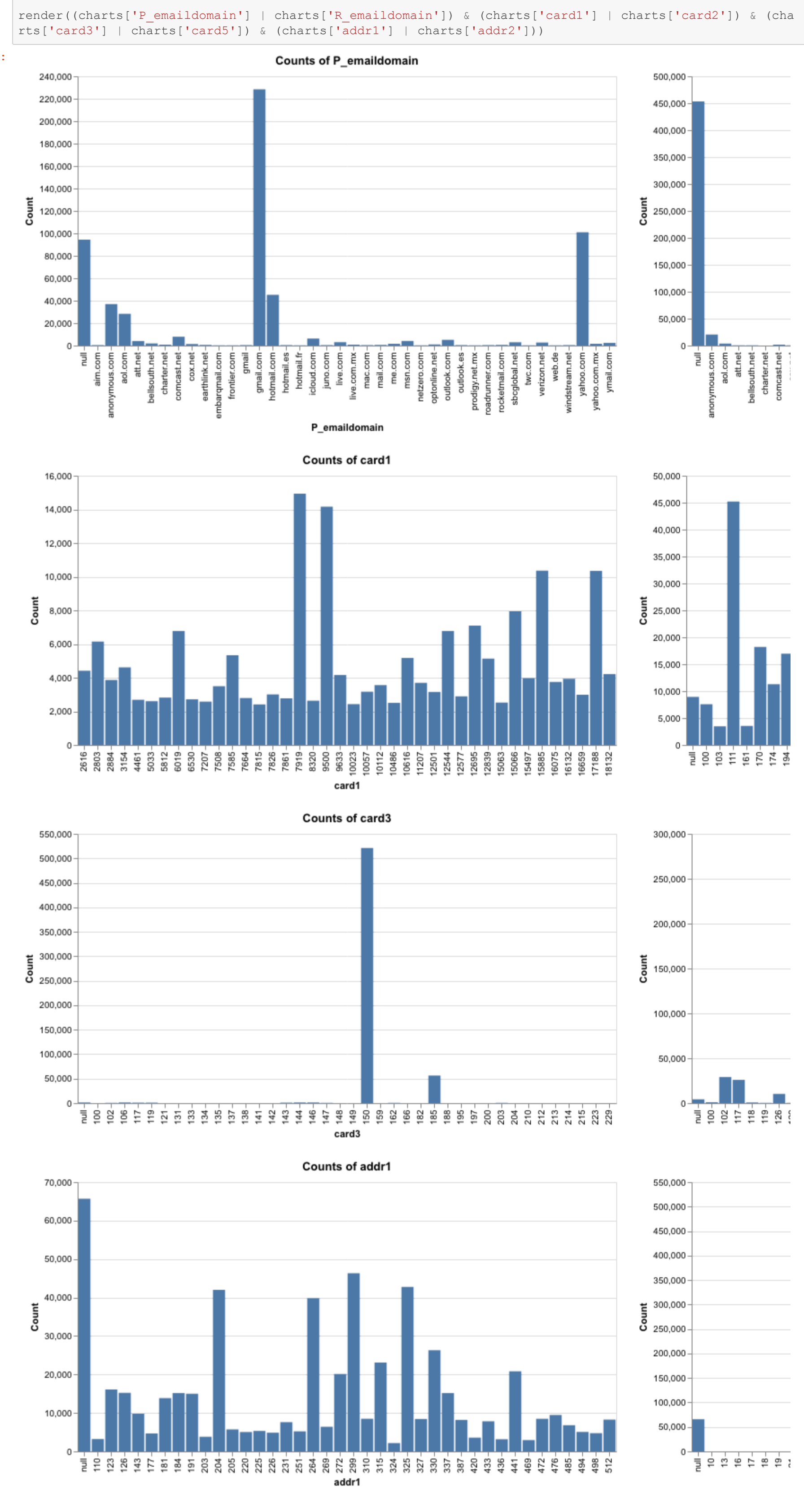
So `card6` is type of card, `card4` is credit card company

In [20]:

```python
charts = {}
for i in ['P_emaildomain', 'R_emaildomain', 'card1', 'card2', 'card3',  'card5', 'addr1', 'addr2']:
    feature_count = train[i].value_counts(dropna=False).reset_index()[:40].rename(columns={i: 'count', 'index': i})
    chart = alt.Chart(feature_count).mark_bar().encode(
                x=alt.X(f"{i}:N", axis=alt.Axis(title=i)),
                y=alt.Y('count:Q', axis=alt.Axis(title='Count')),
                tooltip=[i, 'count']
            ).properties(title=f"Counts of {i}", width=600)
    charts[i] = chart

render((charts['P_emaildomain'] | charts['R_emaildomain']) & (charts['card1'] | charts['card2']) & (charts['card3'] | charts['card5']) & (charts['addr1'] | charts['addr2']))
```

Out[20]:



Feature engineering

Let's create some aggregations. There is no logic in them - simply aggregations on top features.

In [21]:

```python
train['TransactionAmt_to_mean_card1'] = train['TransactionAmt'] / train.groupby(['card1'])['TransactionAmt'].transform('mean')
train['TransactionAmt_to_mean_card4'] = train['TransactionAmt'] / train.groupby(['card4'])['TransactionAmt'].transform('mean')
train['TransactionAmt_to_std_card1'] = train['TransactionAmt'] / train.groupby(['card1'])['TransactionAmt'].transform('std')
train['TransactionAmt_to_std_card4'] = train['TransactionAmt'] / train.groupby(['card4'])['TransactionAmt'].transform('std')

test['TransactionAmt_to_mean_card1'] = test['TransactionAmt'] / test.groupby(['card1'])['TransactionAmt'].transform('mean')
test['TransactionAmt_to_mean_card4'] = test['TransactionAmt'] / test.groupby(['card4'])['TransactionAmt'].transform('mean')
test['TransactionAmt_to_std_card1'] = test['TransactionAmt'] / test.groupby(['card1'])['TransactionAmt'].transform('std')
test['TransactionAmt_to_std_card4'] = test['TransactionAmt'] / test.groupby(['card4'])['TransactionAmt'].transform('std')

train['id_02_to_mean_card1'] = train['id_02'] / train.groupby(['card1'])['id_02'].transform('mean')
train['id_02_to_mean_card4'] = train['id_02'] / train.groupby(['card4'])['id_02'].transform('mean')
train['id_02_to_std_card1'] = train['id_02'] / train.groupby(['card1'])['id_02'].transform('std')
train['id_02_to_std_card4'] = train['id_02'] / train.groupby(['card4'])['id_02'].transform('std')

test['id_02_to_mean_card1'] = test['id_02'] / test.groupby(['card1'])['id_02'].transform('mean')
test['id_02_to_mean_card4'] = test['id_02'] / test.groupby(['card4'])['id_02'].transform('mean')
test['id_02_to_std_card1'] = test['id_02'] / test.groupby(['card1'])['id_02'].transform('std')
test['id_02_to_std_card4'] = test['id_02'] / test.groupby(['card4'])['id_02'].transform('std')

train['D15_to_mean_card1'] = train['D15'] / train.groupby(['card1'])['D15'].transform('mean')
train['D15_to_mean_card4'] = train['D15'] / train.groupby(['card4'])['D15'].transform('mean')
train['D15_to_std_card1'] = train['D15'] / train.groupby(['card1'])['D15'].transform('std')
train['D15_to_std_card4'] = train['D15'] / train.groupby(['card4'])['D15'].transform('std')

test['D15_to_mean_card1'] = test['D15'] / test.groupby(['card1'])['D15'].transform('mean')
test['D15_to_mean_card4'] = test['D15'] / test.groupby(['card4'])['D15'].transform('mean')
test['D15_to_std_card1'] = test['D15'] / test.groupby(['card1'])['D15'].transform('std')
test['D15_to_std_card4'] = test['D15'] / test.groupby(['card4'])['D15'].transform('std')

train['D15_to_mean_addr1'] = train['D15'] / train.groupby(['addr1'])['D15'].transform('mean')
train['D15_to_mean_addr2'] = train['D15'] / train.groupby(['addr2'])['D15'].transform('mean')
train['D15_to_std_addr1'] = train['D15'] / train.groupby(['addr1'])['D15'].transform('std')
train['D15_to_std_addr2'] = train['D15'] / train.groupby(['addr2'])['D15'].transform('std')

test['D15_to_mean_addr1'] = test['D15'] / test.groupby(['addr1'])['D15'].transform('mean')
test['D15_to_mean_addr2'] = test['D15'] / test.groupby(['addr2'])['D15'].transform('mean')
test['D15_to_std_addr1'] = test['D15'] / test.groupby(['addr1'])['D15'].transform('std')
test['D15_to_std_addr2'] = test['D15'] / test.groupby(['addr2'])['D15'].transform('std')
```

In [22]:

```python
train[['P_emaildomain_1', 'P_emaildomain_2', 'P_emaildomain_3']] = train['P_emaildomain'].str.split('.', expand=True)
train[['R_emaildomain_1', 'R_emaildomain_2', 'R_emaildomain_3']] = train['R_emaildomain'].str.split('.', expand=True)
test[['P_emaildomain_1', 'P_emaildomain_2', 'P_emaildomain_3']] = test['P_emaildomain'].str.split('.', expand=True)
test[['R_emaildomain_1', 'R_emaildomain_2', 'R_emaildomain_3']] = test['R_emaildomain'].str.split('.', expand=True)
```

Prepare data for modelling

In [23]:

```python
many_null_cols = [col for col in train.columns if train[col].isnull().sum() / train.shape[0] > 0.9]
many_null_cols_test = [col for col in test.columns if test[col].isnull().sum() / test.shape[0] > 0.9]
```

In [24]:

```python
big_top_value_cols = [col for col in train.columns if train[col].value_counts(dropna=False, normalize=True).values[0] > 0.9]
big_top_value_cols_test = [col for col in test.columns if test[col].value_counts(dropna=False, normalize=True).values[0] > 0.9]
```

In [25]:

```python
cols_to_drop = list(set(many_null_cols + many_null_cols_test + big_top_value_cols + big_top_value_cols_test + one_value_cols+ one_value_cols_test))
cols_to_drop.remove('isFraud')
len(cols_to_drop)
```

Out[25]: 84

In [26]:

```python
train = train.drop(cols_to_drop, axis=1)
test = test.drop(cols_to_drop, axis=1)
```

In [27]:

```python
cat_cols = ['id_12', 'id_13', 'id_14', 'id_15', 'id_16', 'id_17', 'id_18', 'id_19', 'id_20', 'id_21', 'id_22', 'id_23', 'id_24', 'id_25', 'id_26', 'id_27', 'id_28', 'id_29',
            'id_30', 'id_31', 'id_32', 'id_33', 'id_34', 'id_35', 'id_36', 'id_37', 'id_38', 'DeviceType', 'DeviceInfo', 'ProductCD', 'card4', 'card6', 'M4','P_emaildomain',
            'R_emaildomain', 'card1', 'card2', 'card3',  'card5', 'addr1', 'addr2', 'M1', 'M2', 'M3', 'M5', 'M6', 'M7', 'M8', 'M9',
            'P_emaildomain_1', 'P_emaildomain_2', 'P_emaildomain_3', 'R_emaildomain_1', 'R_emaildomain_2', 'R_emaildomain_3']
for col in cat_cols:
    if col in train.columns:
        le = LabelEncoder()
        le.fit(list(train[col].astype(str).values) + list(test[col].astype(str).values))
        train[col] = le.transform(list(train[col].astype(str).values))
        test[col] = le.transform(list(test[col].astype(str).values))
```

In [28]:

```python
X = train.sort_values('TransactionDT').drop(['isFraud', 'TransactionDT', 'TransactionID'], axis=1)
y = train.sort_values('TransactionDT')['isFraud']
#X_test = test.sort_values('TransactionDT').drop(['TransactionDT', 'TransactionID'], axis=1)
X_test = test.drop(['TransactionDT', 'TransactionID'], axis=1)
del train
test = test[["TransactionDT", 'TransactionID']]
```

In [29]:

```python
# by https://www.kaggle.com/dimartinot
def clean_inf_nan(df):
    return df.replace([np.inf, -np.inf], np.nan)

# Cleaning infinite values to NaN
X = clean_inf_nan(X)
X_test = clean_inf_nan(X_test )
```

In [30]:

```python
gc.collect()
```

Out[30]: 47

LGBM

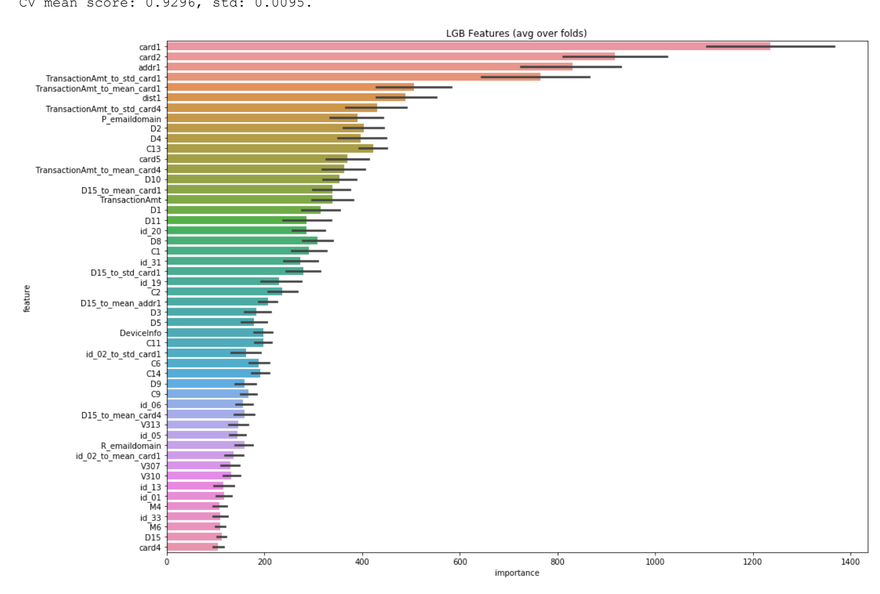
In [31]:

```python
n_fold = 5
folds = TimeSeriesSplit(n_splits=n_fold)
folds = KFold(n_splits=5)
```

In [32]:

```python
params = {'num_leaves': 256,
          'min_child_samples': 79,
          'objective': 'binary',
          'max_depth': 13,
          'learning_rate': 0.03,
          "boosting_type": "gbdt",
          "subsample_freq": 3,
          "subsample": 0.9,
          "bagging_seed": 11,
          "metric": 'auc',
          "verbosity": -1,
          'reg_alpha': 0.3,
          'reg_lambda': 0.3,
          'colsample_bytree': 0.9,
          #'categorical_feature': cat_cols
         }
result_dict_lgb = train_model_classification(X=X, X_test=X_test, y=y, params=params, folds=folds, model_type='lgb', eval_metric='auc', plot_feature_importance=True,
                                                      verbose=500, early_stopping_rounds=200, n_estimators=5000, averaging='usual', n_jobs=-1)
```

```
Fold 1 started at Tue Sep  3 02:30:40 2019
Training until validation scores don't improve for 200 rounds.
[500]   training's auc: 0.994129        training's auc: 0.994129        valid_1's auc: 0.91933  valid_1's auc: 0.91933
Early stopping, best iteration is:
[513]   training's auc: 0.994404        training's auc: 0.994404        valid_1's auc: 0.919435 valid_1's auc: 0.919435
Fold 2 started at Tue Sep  3 02:42:12 2019
Training until validation scores don't improve for 200 rounds.
[500]   training's auc: 0.994715        training's auc: 0.994715        valid_1's auc: 0.931595 valid_1's auc: 0.931595
Early stopping, best iteration is:
[546]   training's auc: 0.995664        training's auc: 0.995664        valid_1's auc: 0.931982 valid_1's auc: 0.931982
Fold 3 started at Tue Sep  3 02:54:10 2019
Training until validation scores don't improve for 200 rounds.
[500]   training's auc: 0.994741        training's auc: 0.994741        valid_1's auc: 0.926174 valid_1's auc: 0.926174
Early stopping, best iteration is:
[372]   training's auc: 0.990799        training's auc: 0.990799        valid_1's auc: 0.926607 valid_1's auc: 0.926607
Fold 4 started at Tue Sep  3 03:03:28 2019
Training until validation scores don't improve for 200 rounds.
[500]   training's auc: 0.994673        training's auc: 0.994673        valid_1's auc: 0.946452 valid_1's auc: 0.946452
Early stopping, best iteration is:
[464]   training's auc: 0.993779        training's auc: 0.993779        valid_1's auc: 0.946655 valid_1's auc: 0.946655
Fold 5 started at Tue Sep  3 03:13:55 2019
Training until validation scores don't improve for 200 rounds.
[500]   training's auc: 0.995027        training's auc: 0.995027        valid_1's auc: 0.922803 valid_1's auc: 0.922803
Early stopping, best iteration is:
[405]   training's auc: 0.992298        training's auc: 0.992298        valid_1's auc: 0.923309 valid_1's auc: 0.923309
CV mean score: 0.9296, std: 0.0095.
```



In [33]:

```python
sub['isFraud'] = result_dict_lgb['prediction']
sub.to_csv('submission.csv', index=False)
```

In [34]:

```python
sub.head()
```

Out[34]:

	TransactionID	isFraud
0	3663549	0.001571974543870
1	3663550	0.001823337471988
2	3663551	0.003487491775315
3	3663552	0.001593888169964
4	3663553	0.002441269688730

In [35]:

```python
pd.DataFrame(result_dict_lgb['oof']).to_csv('lgb_oof.csv', index=False)
```

Blending

In [36]:

```python
# xgb_params = {'eta': 0.04,
#               'max_depth': 5,
#               'subsample': 0.85,
#               'objective': 'binary:logistic',
#               'eval_metric': 'auc',
#               'silent': True,
#               'nthread': -1,
#               'tree_method': 'gpu_hist'}
# result_dict_xgb = train_model_classification(X=X, X_test=X_test, y=y, params=xgb_params, folds=folds, model_type='xgb', eval_metric='auc', plot_feature_importance=False,
#                                                       verbose=500, early_stopping_rounds=200, n_estimators=5000, averaging='rank')
```

In [37]:

```python
# test = test.sort_values('TransactionDT')
# test['prediction'] = result_dict_xgb['prediction']
# sub['isFraud'] = pd.merge(sub, test, on='TransactionID')['prediction']
# sub.to_csv('submission_xgb.csv', index=False)
```

In [38]:

```python
# test = test.sort_values('TransactionDT')
# test['prediction'] = result_dict_lgb['prediction'] + result_dict_xgb['prediction']
# sub['isFraud'] = pd.merge(sub, test, on='TransactionID')['prediction']
# sub.to_csv('blend.csv', index=False)
```