

WEEK 12 Deploying and Monitoring a Model for Banking Customer Churn Prediction

The most effective method for deploying a model to predict banking customer churn depends on the specific problem statement and business requirements. Both batch and real-time deployment approaches have their pros and cons.

Batch deployment involves running the model on a batch of data, typically collected over a period of time, and making predictions in bulk. This approach is suitable when the predictions of customer churn does not require real-time or near-real-time decision-making is not required for customer churn predictions, and when the data used for predictions is relatively stable over time. Batch deployment can be efficient in terms of computational resources as it allows for batch processing and can handle large volumes of data at once. On the other hand, real-time deployment involves making predictions in real-time or near-real-time as new data becomes available. This approach is suitable when timely and immediate action is required based on the churn prediction results, such as sending targeted offers or alerts to customers at risk of churning. Real-time deployment can be beneficial in situations where prompt actions can potentially prevent customer churn or minimize its impact.

Putting machine learning models into production is a great achievement. However, the performance of models may degrade over time due to a concept called “model drift”. Our model in production is constantly receiving new data to make predictions upon, but this data might have a different probability distribution than the one we trained the model on. Using the original model with the new data distribution will cause a drop in model performance. To avoid performance degradation, it is necessary to monitor the changes in our model’s performance. Model drift can be categorized into two broad categories: concept drift and data drift.

Data drift is the situation where the model’s input distribution changes. Concept stands for the joint probability distribution of a machine learning model’s inputs (X) and outputs (Y). The cause of the relationship change is usually some kind of external event/process or change in the real world. Data drift or concept drift can occur in the banking customer churn prediction model if there are changes

in customer behavior, market dynamics, or business strategies that affect the underlying patterns in the data.

To effectively mitigate the risks associated with model drift, it is imperative to regularly monitor key aspects such as data distribution, feature importance, and model performance. This can be achieved by utilizing performance metrics such as accuracy, precision, and a variety of statistical measures. Additionally, business metrics such as customer churn rate, customer retention rate, customer lifetime value, and revenue impact can provide valuable insights into the performance of the model. User feedback can also be utilized as a source of information to detect model drift, although it is not ideal for users to experience degraded model performance before drift is detected, especially in high-value models. Therefore, it is crucial to establish monitoring thresholds to alert when the model's behavior deviates significantly from expected values during a high-performance time period of any environment.

Setting appropriate thresholds for green, yellow, and red flags is essential for effective monitoring. These thresholds should be based on the acceptable range for each performance metric. For example, if the acceptable range for customer churn rate is between 0-5%, a threshold of 5% could be set as the yellow flag indicating that errors should be tracked closely. A threshold of 10% could be set as the red flag indicating that the model should be pulled out of production.

For green flags, regular monitoring and periodic review of model performance should be conducted to ensure that the model is performing well and meeting the desired performance metrics. For yellow flags, closer monitoring, root cause analysis, and potential adjustments for interventions can be implemented to mitigate any issues or errors. For red flags, immediate action should be taken to investigate and address the issues, which may involve stopping the model from production until these issues are resolved.

Once model drift is detected, strategies can be employed to handle it. One strategy is to retrain or adapt the model. If the drift is due to changes in data distribution, the model can be retrained or adapted by adjusting model parameters such as training weights to account for the changes in information carried by the data features. Scheduled model management can also be used for

seasonal drift, where the model is updated periodically to account for changing patterns. Another strategy is to update training data with new data that carries current information about the relationship between the input and output data, and then retrain the model.

The frequency of model retraining depends on the rate of data change and the specific requirements of the use case. If the data for the banking customer churn prediction model is subject to frequent changes, such as changes in customer behavior, market dynamics, or business strategies, more frequent model retraining may be necessary to maintain accuracy and relevance. However, if the data changes are relatively slow, periodic model training, such as monthly or quarterly, may be sufficient.

Dependencies:

Package	Version
absl-py	1.3.0
alembic	1.9.1
anyio	3.6.2
argon2-cffi	21.3.0
argon2-cffi-bindings	21.2.0
arrow	1.2.3
asttokens	2.2.1
astunparse	1.6.3
async-generator	1.10
attrs	22.2.0
Automat	22.10.0
Babel	2.11.0
backcall	0.2.0
beautifulsoup4	4.11.1
binaryornot	0.4.4
bleach	5.0.1
brewer2mpl	1.4.1
brotlipy	0.7.0
cachetools	5.2.1
certifi	2022.12.7
certipy	0.1.3
cffi	1.14.6
chardet	4.0.0

charset-normalizer	2.0.0
click	8.1.3
cloudpickle	2.2.1
colorama	0.4.4
comm	0.1.2
conda	4.10.3
conda-package-handling	1.7.3
constantly	15.1.0
contourpy	1.0.6
cookiecutter	2.1.1
cryptography	3.4.8
cssselect	1.2.0
cycler	0.11.0
debugpy	1.6.5
decorator	5.1.1
defusedxml	0.7.1
entrypoints	0.4
executing	1.2.0
fastjsonschema	2.16.2
filelock	3.9.0
flatbuffers	23.1.4
fonttools	4.38.0
fst-pso	1.8.1
FuzzyTM	2.0.5
gast	0.4.0
gensim	4.3.0
ggplot	0.11.5
google-auth	2.16.0
google-auth-oauthlib	0.4.6
google-pasta	0.2.0
graphviz	0.20.1
greenlet	2.0.1
grpcio	1.51.1
h5py	3.7.0
hyperlink	21.0.0
idna	3.1
imageio	2.24.0
imbalanced-learn	0.10.1
importlib-metadata	6.0.0
incremental	22.10.0
ipykernel	6.19.4

ipython	8.8.0
ipython-genutils	0.2.0
ipywidgets	7.7.2
itemadapter	0.7.0
itemloaders	1.0.6
jedi	0.18.2
Jinja2	3.1.2
jinja2-time	0.2.0
jmespath	1.0.1
joblib	1.2.0
json5	0.9.11
jsonschema	4.17.3
jupyter_client	7.4.8
jupyter_core	5.1.2
jupyter-resource-usage	0.6.4
jupyter-server	1.23.4
jupyter-telemetry	0.1.0
jupyterhub	1.5.1
jupyterlab	3.5.2
jupyterlab-pygments	0.2.2
jupyterlab_server	2.18.0
jupyterlab-widgets	1.1.1
keras	2.11.0
kiwisolver	1.4.4
libclang	15.0.6.1
llvmlite	0.39.1
lxml	4.9.2
Mako	1.2.4
mamba	0.16.0
Markdown	3.4.1
MarkupSafe	2.1.1
matplotlib	3.6.2
matplotlib-inline	0.1.6
miniful	0.0.6
mistune	2.0.4
nbclassic	0.4.8
nbclient	0.7.2
nbconvert	7.2.7
nbformat	5.7.1
nbgitpuller	1.1.1
nest-asyncio	1.5.6

networkx	3.0
nltk	3.8.1
notebook	6.5.2
notebook_shim	0.2.2
nteract-on-jupyter	2.1.3
numba	0.56.4
numpy	1.23.5
nvidia-cublas-cu11	11.10.3.66
nvidia-cuda-nvrtc-cu11	11.7.99
nvidia-cuda-runtime-cu11	11.7.99
nvidia-cudnn-cu11	8.5.0.96
oauthlib	3.2.2
opencv-python	4.7.0.68
opt-einsum	3.3.0
packaging	22.0
pamela	1.0.0
pandas	1.5.2
pandocfilters	1.5.0
parsel	1.7.0
parso	0.8.3
patsy	0.5.3
pexpect	4.8.0
pickleshare	0.7.5
Pillow	9.4.0
pip	21.3
platformdirs	2.6.2
plotly	5.11.0
prometheus-client	0.15.0
prompt-toolkit	3.0.36
Protego	0.2.1
protobuf	3.19.6
psutil	5.9.4
ptyprocess	0.7.0
pure-eval	0.2.2
pyasn1	0.4.8
pyasn1-modules	0.2.8
pycosat	0.6.3
pycparser	2.20
pydataset	0.2.0
PyDispatcher	2.0.6
pydot	1.4.2

pydotplus	2.0.2
pyFUME	0.2.25
Pygments	2.14.0
pyOpenSSL	21.0.0
pyparsing	3.0.9
pyrsistent	0.19.3
PySocks	1.7.1
python-dateutil	2.8.2
python-json-logger	2.0.4
python-slugify	7.0.0
pytz	2022.7
PyWavelets	1.4.1
PyYAML	6.0
pyzmq	24.0.1
queuelib	1.6.2
regex	2022.10.31
requests	2.28.1
requests-file	1.5.1
requests-oauthlib	1.3.1
rsa	4.9
ruamel.yaml	0.17.21
ruamel.yaml.clib	0.2.7
ruamel.yaml-conda	0.15.80
scikit-image	0.19.3
scikit-learn	1.2.0
scipy	1.10.0
Scrapy	2.7.1
seaborn	0.12.2
Send2Trash	1.8.0
service-identity	21.1.0
setuptools	58.2.0
shap	0.41.0
simpful	2.9.0
SimpleCV	1.3
six	1.16.0
slicer	0.0.7
smart-open	6.3.0
sniffio	1.3.0
soupsieve	2.3.2.post1
SQLAlchemy	1.4.46
stack-data	0.6.2

statsmodels	0.13.5
tenacity	8.1.0
tensorboard	2.11.0
tensorboard-data-server	0.6.1
tensorboard-plugin-wit	1.8.1
tensorflow	2.11.0
tensorflow-estimator	2.11.0
tensorflow-io-gcs-filesystem	0.29.0
termcolor	2.2.0
terminado	0.17.1
text-unidecode	1.3
threadpoolctl	3.1.0
tifffile	2022.10.10
tinycss2	1.2.1
tldextract	3.4.0
tomli	2.0.1
torch	1.13.1
torchvision	0.14.1
tornado	6.2
tqdm	4.62.3
traitlets	5.8.0
Twisted	22.10.0
typing_extensions	4.4.0
urllib3	1.26.7
w3lib	2.1.1
wcwidth	0.2.5
webencodings	0.5.1
websocket-client	1.4.2
Werkzeug	2.2.2
wheel	0.37.0
widetsnbextension	3.6.1
wrapt	1.14.1
xgboost	1.7.3
zipp	3.11.0
zope.interface	5.5.2