IN-Season Price Optimization Model Handbook

This model forecast sales qty at SKU or STYLE level on a select day with MARKDOWN for each product as a given knowledge.

Global parameters

- pass_days: 提前多少天预测目标日期的销量
- fcst_date: 预测的目标日期,没有可填写一个数据没有的日期,或""
- rm_dates: retail moment dates, 在是否预测retail moments和计算历史销量变量是否考虑 retail moments会用到
- PE: Product Engine(FTW)
- use_platform: TMALL
- paths: 路径管理工具
 - paths.source: 原始从DB中取到的数
 - paths.step data: 对source的数处理后的数据
 - paths.style model/paths.sku model: 模型数据

global parameters中的pass days/rm dates/paths在config.py中定义,这些参数会影响到 后面每个code file的运行,务必在运行前确认或修改,并且在运行各代码文件时保持一致; 另外重要的原始数据文件的文件名也在config.py中定义

Running Procedures

Step1. 从DB取transaction+attribute+inventory的数据,合并

- Code File: 1 md sensitivity model data init include sql.py
- Key Parameters:
 - 。 data_end_date: 取数的截止日期
 - pass_days: global parameter
 - rm_dates: global parameter
 - use_platform: TMALL
 - 1. 取数的逻辑是先从存量(之前处理好的)数据中读取数据最后的日期,作为data start date, 从数据库取data start date至data end date之间的数据,拼接好后,续到存量数 据后,再存于本地 (如果只有训练数据可以直接覆盖原存量数据文件)
 - 2. 如果是预测数据,需要将预测日期的产品,折扣,MSRP,是否inseason等信息,事先 存到一张表,merge 完product attribute等信息之后,append到之前的存量数据后,存 到一个新的文件,不要直接覆盖原存量数据,因为预测日期的md并非真实, sales_qty, sales_amt也不存在,**存量数据用于存放真实已发生的数据**

· Data files:

- 存量模型训练数据 (输入): step data/tmall sku daily data master fcst.csv
- MPM product attributrs(输入)
 每个season一张表,需要及时找Will Sun要最新season的
- **更新日期后的模型训练数据(输出):** step_data/tmall_sku_daily_data_master_fcst.csv 如果只需要训练模型,不需要下面两步,这一步的结果可以直接作为后面程序的输入
- 预测当天的产品数据 (输入): step data/plan 99 products.csv 仅包含99的产品
- **模型预测的输入数据 (输出)**: step_data/fcst_20200720.csv 存量训练数据+merge了 product attribute和inventory的预测产品数据,如果需要做预测,这一步的结果是后面程序文件的输入
- 本地库存数据 (输出): inventory data.csv 也会随着日期更新被更新
- retail moment销售数据(输出): 会作为3_zx_rm_features.py的输入, 计算历史大促相关的特征

Step2. Feature Engineering

特征工程Part分为三块代码, 需要依次运行

- 2_Sophie_feature_engineering_style(sku).py
- 3_zx_rm_features.py (can skip if forecast non-retail moment)
- 4_md_sensitivity_style_99_doc.py

2.1 Sophie features:

分为style和sku两个版本

- · Code File:
 - 2 Sophie feature engineering style(sku).py
- Input Data:
 - data_master_include_forecast_day (fcst_20200720.csv):训练/预测数据, Step1的结果
 - o sophie_features_src / sophie_features_sku_src (20200711df_style.csv/20200714df_sku.csv):
 Sophie features的存量feature数据
- Key Parameters:
 - 。 code_start_date: 需要重新计算feature的起始日期
 - 。 code_end_date: 需要重新计算feature的终止日期
 - excl_rm: 是否需要在计算feature是把rm_dates去除,即计算历史销量的时候不考虑 retail moments时的销量
 - fcst_date: global parameter
 - PE: product engine

Output Data:

updated sophie_features_src / sophie_features_sku_src (20200711df_style.csv/20200714df_sku.csv)
 by sku/style by date by inseason_flag1 的features

如果本地存量数据中含有上次预测日的数据,则需要将上次预测日的特征重新计算,e.g.设置code_start_date/小于上次预测日,即可覆盖上次预测日的特征

2.2 Retail Moment Features

Retail-moment related features for forecasting retail moments only These features will be **NAN** for non-retail moment days

- Code File
 - o 3 zx rm features.py
- Input Data:
 - local_retail_moment_only_data_src: retail moments transaction data
 - data_master_include_forecast_day: this data is only used for getting DIVISION(FTW/APP/EQP)
 - rm_calendar: retail moment calendar, this file need to be manually maintained when new retail moments are settled

sales_date	RM_name	number	day_number
2017-03-06	38女王节	1	1
2017-03-07	38女王节	1	2
2017-03-08	38女王节	1	3
2017-06-18	618大促	2	1
2017-06-19	618大促	2	2
2017-06-20	618大促	2	3
2017-09-09	99大促	3	1
2017-09-10	99大促	3	2
2017-11-11	11.11	4	1
2017-12-12	12.12	5	1
2018-03-07	38女王节	6	1
2018-03-08	38女王节	6	2
2018-03-09	38女王节	6	3
2018-06-01	618大促	7	1

Key Parameters

PE: product engine

use_platform: TMALL

• level: sku or style

Output Data

• zx_rm_sku(style)_features: retail moment related features

2.3 Get All Features Ready

- Code File:
 - 4_md_sensitivity_style_99_doc.py (Initial setup + Step 1)
- Key Parameters:
 - PE: product engine

- fcst_date: global parameter
- fcst_level: sku/style sku level的预测还是style level的预测
- 。 season_rm_dict: defined in config.py, 每个season retail moment的起始日期,用于计算距离retail moment的天数,如果这个season没有retail moment可不运行
- fcst_date_site_traffic: 预测当天的traffic预测值,如果不需要或者traffic数据文件中已有,可设置成None

· Key Functions:

- prepare_modeling_data: 用于计算新的features以及merge上两步的features
- 。 cal_days_from_rm: 计算距离retail moment的天数,如果这个season没有retail moment可不运行

• Input Data:

- o data_master_include_forecast_day: (fcst 20200720.csv) Step1的输出
- o competing_styles/skus_existing_features: 本地存量competing-product features
- 。 sku_color_features_to_date: 本地存量颜色变量
- md_sensitivity_model_traffic_file: daily site traffic, 如果数据中包含未来要预测的数据,则需要保证traffic文件中包含未来预测那天的traffic预测值或者把值给到变量fcst date site traffic
- 前面两步的输出(Sophie's features and Zhaoxu's rm features if needed)

Output Data:

- md_sensitivity_model_master_file: feature engineering finished and ready for modeling or forecasting
- 。 变量列表及解释: \feature engineering\20200526_FeatureEngineering_master.xlsx
- 1. 如果pass_days不变,可以只计算增量日期的features,但是<mark>增量时间范围包含的sku/style</mark>的历史数据必须也加起来算增量日期的特征
- 2. 如果pass days改变了,那么存量数据亦需要重新计算特征

Step3. Model Training

• Code File: 4 md sensitivity style 99 doc.py (Initial setup + Step 2)

3.1 Filter modeling target

• Key Parameters:

- train_seasons: SP/SU/FA/HO select season for training model
- rm_remove: False if forecast retail moment days, otherwise True
- off_season_remove: True if only forecast in-season products, otherwise False
- full_price_remove: True if only forecast discounted products(md>=0.05), otherwise False
- exclude_date_since: if use only FA2018, FA2019 to train model, but with data longer than that, then set this date to '2020-01-01' can exclude 2020 data when modeling
- **Key Function**: filter_modeling_data
- Input Data: md_sensitivity_model_master_file (Step2 output)

3.2 Run model and check result

• Key Parameters:

- y_denom: This model forecast sales boost, which is the sales qty of a target day over previous sales performance, so y_denom defines denominator of sales boost. Currently, past 3 days median sales qty is used as denominator
- y_numer: sales qty of the forecast target day
- model_params: This model is a tree-based model. This param defines learning rate, n_estimators, depth, number of leaves
- train_test_ratio: train dataset size/available dataset size
- Key Function: run_model
- Key Output:
 - Performance Indices:
 - Sales qty MAPE of test data per day per product
 - Sales qty percentage of MAPE within 30%
 - Frequency percentage of MAPE with 30%
 - Sales boost accuracy matrix
 - Numerical features distribution
 - Finalized Model for next-level forecasting
 - Used features in Model
 - Predict result of test dataset
 - Feature importance(in predict result file)
 - fcst_result
 features_check.xlsx
 md_sensitivity_0.95.pkl
 md_sensitivity_0.95_features.xlsx
 model_data.xlsx
 predict_result_0.95.xlsx
 train_model_performance.JPG
 model_params.json

Step4. Forecasting

- Key Parameters:
 - o is_forecast: True
 - fcst_date: global parameter
 - train_test_ratio: for select model file only, model is named with train test ratio
- Key Function:
 - filter_modeling_data: for select in-season/off-season status, whether contains full
 price products
 - ModelData: prepare modeling data
 - MDModel: load model and make forecast
- Input Data: md_sensitivity_model_master_file (Step2 output)
- Output Data: forecast result with modeling attributes

如果模型早已训练好,只想加工预测数据的特征,Sophie的feature部分依然需要把所有产品的历史数据都准备好作为code的输入,但是通过修改code_start_date, code_end_date 都等于 fcst_date, 可以只计算预测数据的特征; Ruofei的feature部分可以只把预测当天所涉及到的产品的历史数据先取出,再run prepare_modeling_data , 然后只取 sales_date=fcst_date的部分,就是预测数据的特征