

# Food Demand Forecast

## Business, Economic and Financial Data Project

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# Modelling

Since we want to organize the goods for each specific fulfillment center, we need to forecast the demand for each specific center. Moreover, we also need to stratify for each unique meal, since each of them requires a different set of raw materials. We propose a two-stage approach:

- First we account for the temporal relationship using the linear model, obtaining (hopefully) i.i.d. residuals
- Then we model the obtained residuals, using some flexible method such as the gradient boosting

## Linear model

We want to fit a straight line, between demand and time, for each combination of center and meal. This mean we should fit  $N^o centers \cdot N^o meals$  ( $77 \cdot 51 = 3927$ ) linear models. But if we carefully craft some indicator variables we can specify all the simple linear models in to one single big linear model.

## Linear model

$$Y_{ij} = \beta_{0ij} + \beta_{1ij}week + \varepsilon_{ij}$$

$$\forall i = 1, \dots, 77; j = 1, \dots, 51$$

Is equivalent to:

$$Y = \beta_0 + \beta_1 week + X_{ind}\beta_{level} + X_{ind}\beta_{slope} \cdot week + \varepsilon$$

## Linear model

where  $X_{ind}$  is a vector with  $51 \cdot 77 - 1 = 3926$  columns, and is obtained as the interaction between the dummy expansion of the categorical variables `center_id` and `meal_id`.

The model has  $1 + 1 + 3926 + 3926 = 7854$  scalar parameters, that in the simple formulation there are 2 parameters for each model, so  $2 \cdot 77 \cdot 51 = 7854$

# Validation set and Test set

Dealing with time series data means that standard cross validation is not a viable option, since it breaks the temporal dependency. We instead reserved a validation set, taking the last set of observations. The test set are the next 10 weeks, and the true number of orders stands on Kaggle.

# Validation set and Test set



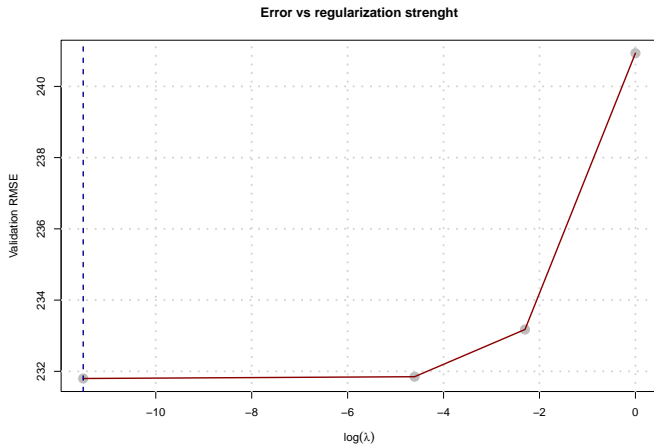
# Regularization

We added elastic-net regularization in the estimation process:

$$\hat{\beta} = \arg \min_{\beta \in \mathbb{R}^p} \left( \sum_{i=1}^n (y_i - x_i^T \beta)^2 + \lambda \sum_{j=1}^p \left( \frac{1}{2} (1 - \alpha) \beta_j^2 + \alpha |\beta_j| \right) \right)$$



# No regularization is needed



## Results on validation set

Model	RMSE	MAE
Mean	350.9743	211.5107
LM	240.9311	106.4178
LM on $\ln(y)$	367.1824	181.3026