

# Meat sales forecasting (Panvita Group)

ESGI SI: European Study Group  
Mathematics With Industry Workshop 2017  
Bled, Slovenia

# Team Members



Coordinator: Alen Vegi Kalamar

Panvita Group: Simon Ravnič

Members: Biljana Zlatanovska  
Limonka Koceva Lazarova  
Mircea Simionica

Mentors: Drago Bokal  
Janja Jerebic

ESGI Slovenia was supported by COST Action TD1409, Mathematics for Industry Network (MI-NET)

# Problem Background



- Meat production
- Goal:
  - Freshly prepared meat for consumers
  - Reduce the quantity of discarded meat
- Solution:
  - Predicting the quantity of meat sold per day
  - The forecasting model for few days ahead

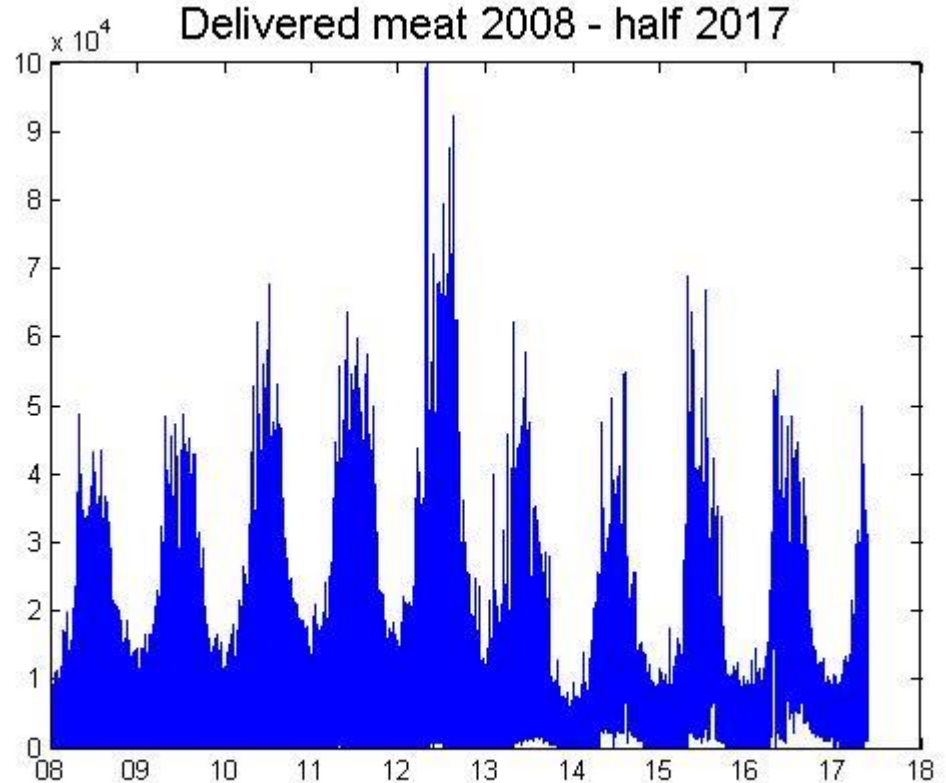
# Problem Procedure

- Worker makes an estimation for the procurement of meat
  - Experience
  - Movement of orders
- The procured meat is processed
  - Expiry date of 8 days
- Transport of prepared meat
- Procedure time: 2 days

# Problem Data

- Daily orders from 2008 onwards
- Daily supply from 2008 onwards
- Clear seasonal patterns with spikes in the summer

ESGI Slovenia was supported by COST Actio



# Bibliography overview

## Modelling techniques:

- Neural Networks (Classical, Adaptive, Fuzzy, Self Organizing Maps, various inputs)
- Regression (linear, logistic, ARIMA, support vector machines),
- Model Trees (Cluster and forecast models),
- Genetic Algorithms (combined with ANN),
- Combinations.

## Input Feature Sets:

- Time  
(month, day of week)
- Autoregressive  
(day before, week before, weeks before)
- Weather  
(temperature, solar irradiation/cloudiness).

# Statistical tools used

- Different models have been employed: Multiple Linear Regression, Support Vector Regression, Autoregressive models
- Goodness of fit benchmarked through Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE)

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right|$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{Y}_i - Y_i)^2}$$

# A starting point ...

Brute force approach: regress, regress some more & check goodness of fit

## MLR models making use of whole data

Description	MAPE	RMSE
MLR + weekdays, months, incomes, holidays (all)	81.92	7158.92
MLR + weekdays, months, incomes, holidays (BIC)	81.68	7167.11
MLR + weekdays, months, incomes, holidays, weather (all)	83.18	7179.68
MLR + weekdays, months, incomes, holidays, weather (BIC)	83.16	7201.38
MLR + weekdays, months, incomes, holidays, weather, supply before (all)	39.18	5140.61
MLR + weekdays, months, incomes, holidays, weather, supply before (BIC)	43.35	5254.39
MLR + months and supply 3, 14, 21 and 28 days before	37.22	5276.60



## Problem data ... a closer look to patterns

Weekday	Week n	Week n + 1
Monday	4933.568	4716.28
Tuesday	7251.472	10411.67
Wednesday	4301.298	5694.955
Thursday	7574.879	9042.782
Friday	10935.74	11492.02
Saturday	4202.074	5455.222
Sunday	0	0

Similar patterns throughout the weeks



Different model for each day of the week?

## MLR models for Monday

Description	MAPE	RMSE
MLR + weekdays, months, incomes, holidays, weather, supply before (all)	56.13	6111.01
MLR + weekdays, months, incomes, holidays, weather, supply before (BIC)	51.30	5459.23
MLR + supply two days before	26.51	5508.53

## MLR models for Friday

Description	MAPE	RMSE
MLR + weekdays, months, incomes, holidays, weather, supply before (all)	18.15	5798.07
MLR + weekdays, months, incomes, holidays, weather, supply before (BIC)	15.01	5421.85
MLR + supply one, two, three, seven and eight days before	10.90	4859.27
MLR + supply one, two, seven and eight days before	10.98	4821.86

# Support Vector Regression (SVR)

## SVR models making use of whole data

Description	MAPE	RMSE
SVR + weekdays, months, incomes, holidays (all)	44,41	6809,05
SVR + weekdays, months, incomes, holidays (BIC)	46,11	6799,67
SVR + weekdays, months, incomes, holidays, weather (all)	45,59	6986,72
SVR + weekdays, months, incomes, holidays, weather (BIC)	43,69	6770,83
SVR + weekdays, months, incomes, holidays, weather, supply before (all)	30,49	5037,80
SVR + weekdays, months, incomes, holidays, weather, supply before (BIC)	29,96	5012,11
SVR + months and supply 3, 14, 21 and 28 days before	33,94	5363,89

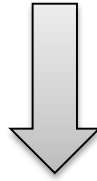
## SVR models for Monday

Description	MAPE	RMSE
SVR + weekdays, months, incomes, holidays, weather, supply before (all)	41.05	4878.24
SVR + weekdays, months, incomes, holidays, weather, supply before (BIC)	53.20	5234.54
SVR + supply two days before	27.34	5450.64

## SVR models for Friday

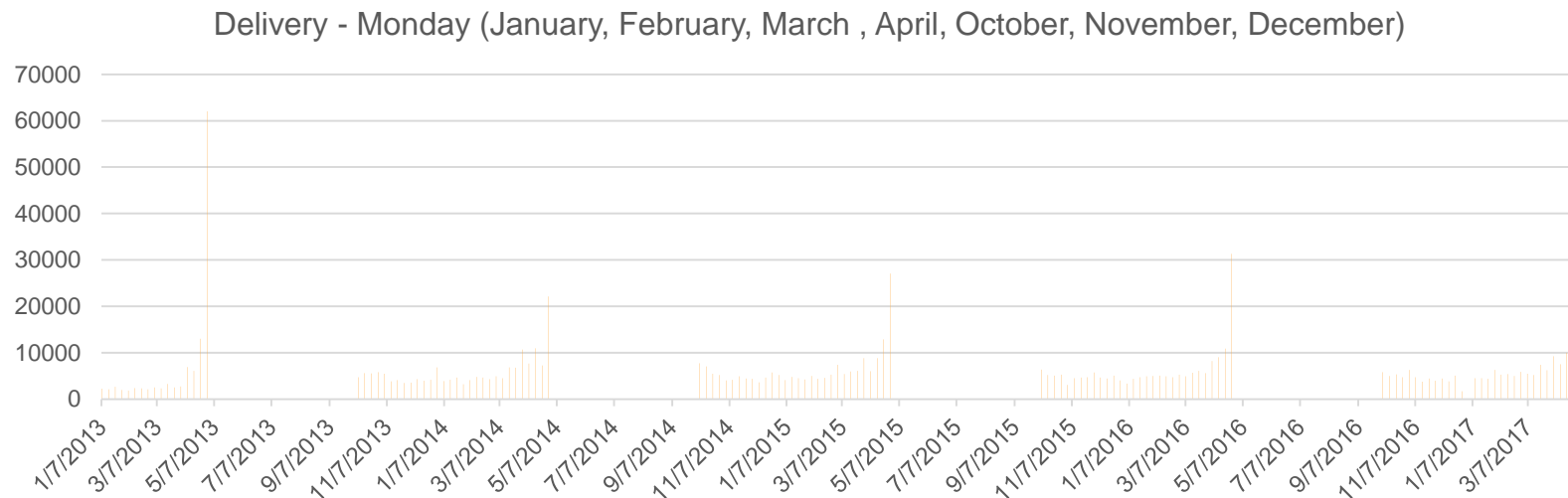
Description	MAPE	RMSE
SVR + weekdays, months, incomes, holidays, weather, supply before (all)	15.69	6600.47
SVR + weekdays, months, incomes, holidays, weather, supply before (BIC)	14.70	5164.36
SVR + supply one, two, three, seven and eight days before	11.46	4124.32
SVR + supply one, two, seven and eight days before	11.55	4311.40

# Alternative approach for future research

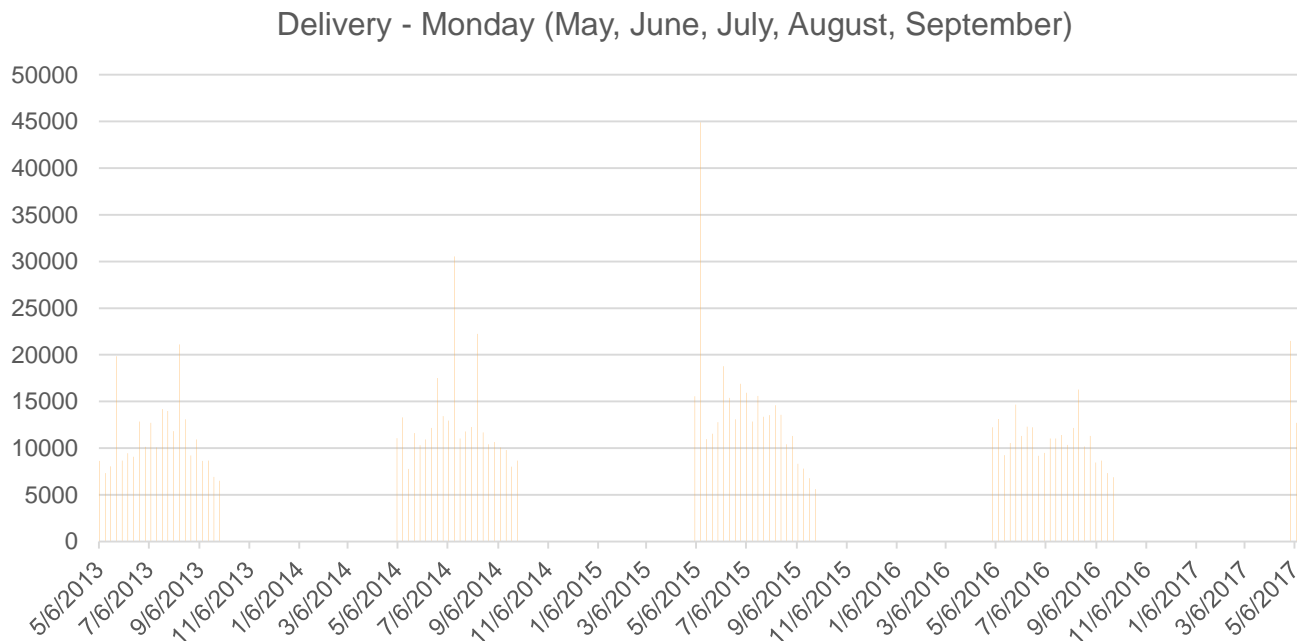


## Season-based models instead of day-based ones

# Problem data ... a closer look to patterns



# Problem data ... a closer look to patterns

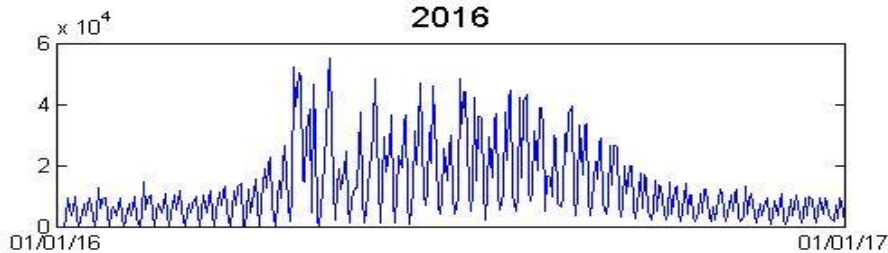
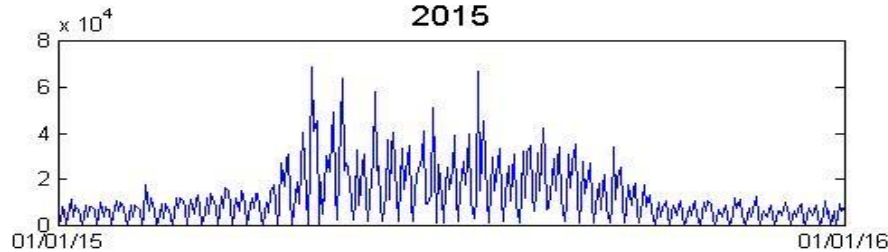


# Autoregressive (ARIMA) models

- They describe a stationary timeseries by means of two polynomials: one AR (autoregressive) and one MA (moving average). AR involves regressing the variable on its own lagged values, while MA models the timeseries through error terms occurring in the past
- Tests with various parametrized ARIMA models have revealed that their power lies in forecasting the data only on short period of times. They are not suitable for long-horizon forecasts.



# Problem data ... another closer look to patterns



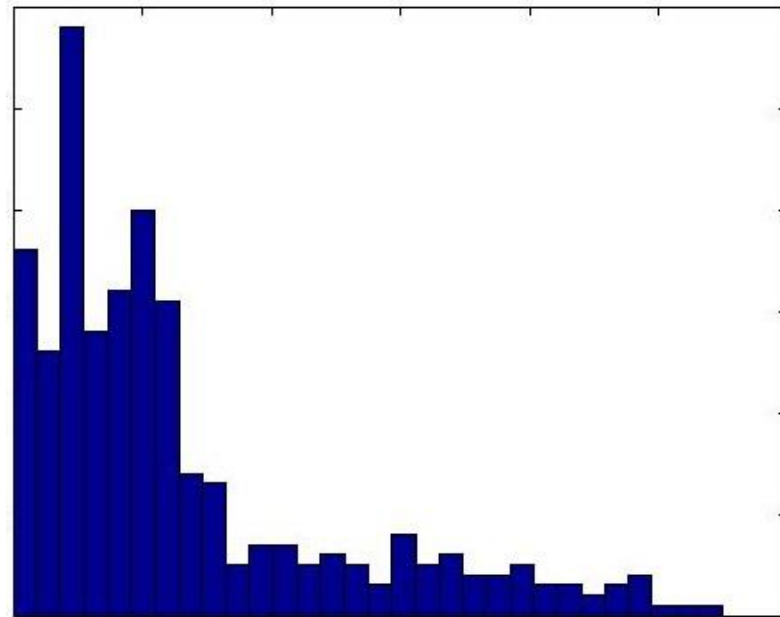
Similar patterns throughout the years



Use past year data to predict current values?

# Adding some stochasticity

Weekday	3° Week 2015	3° Week 2016
Monday	4185.9968	4795.9418
Tuesday	7173.2672	8705.5872
Wednesday	3070.9200	3438.3000
Thursday	6731.0924	8141.1722
Friday	5371.9748	7350.1120
Saturday	5019.3528	6661.0704
Sunday	0.0000	0.0000



Sales distribution in 2016

# Geometric Brownian Motion

Let  $X$  be the delivered quantity and let it be governed by the following stochastic differential equation:

$$dX(t) = \mu(t)X(t)dt + \sigma(t)X(t)dW(t)$$

where  $W(t)$  is a Brownian motion. Then  $X$  is driven by the following relation:

$$X_t = X_{t-\Delta t} e^{\left(\mu_t - \frac{\sigma}{2}\right)\Delta t + \sigma_t \sqrt{\Delta t} Z_t}$$

$X_{t-\Delta t}$  can be the one of the previous year and parameters  $\mu$  and  $\sigma$  can be calibrated on previous month deliveries to keep track of recent developments in the market.

# Thank you for your attention!