

Models to predict client's phone calls to Iberdrola Call Center

VI Modelling Week UCM



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IBERDROLA

1. Problem description

2. Data analysis

3. Modelling

4. Validation and prediction

5. Conclusions and perspectives



1. Problem description

Problem description



- Iberdrola is a company that provides electricity and/or gas to the customers.
- Customers can contact Iberdrola, for instance, by letters, internet and **Phone calls (Call Center)**.
- In a Call Center: to avoid **over-staff** and **under-staff** Iberdrola needs a good prediction about the number of operators.
- **Objective:** Find a model to predict the volume of customer calls.

Problem description



- Forecasting methodology: for operational reasons, **we need to predict the volume of calls for next month, six weeks in advance.**





2. Data analysis



Weekly data

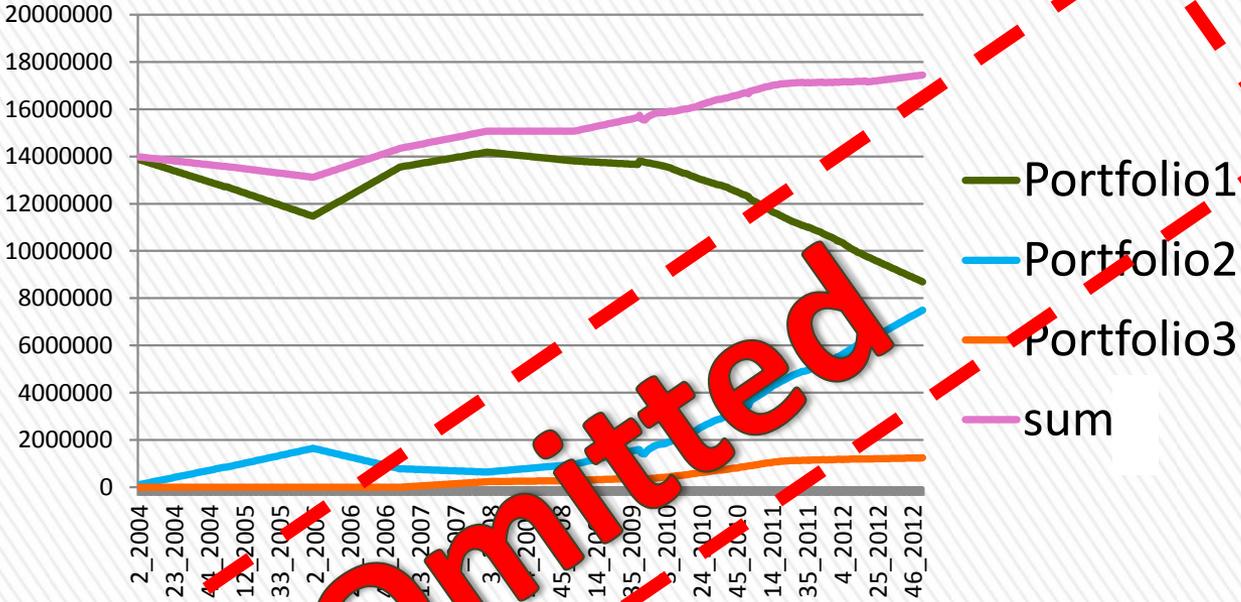
- **Portfolio 1:** regulated market
- **Portfolio 2:** free market
- **Portfolio 3:** gas market (since 01/2007)
- **Bill type 1:** estimated consumption
- **Bill type 2:** real consumption
- **Bill type 3:** fixed quota without consumption
- **Bill type 4:** other (corrections, material, etc.)

Transformed to daily data

Daily data

- **Calls:** number of calls → *target variable*

Data analysis

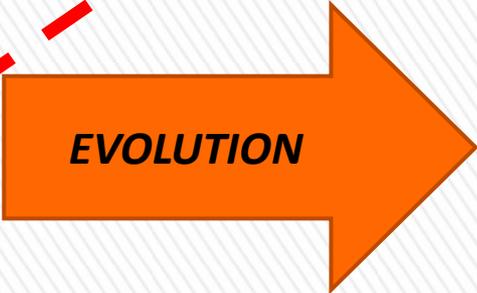
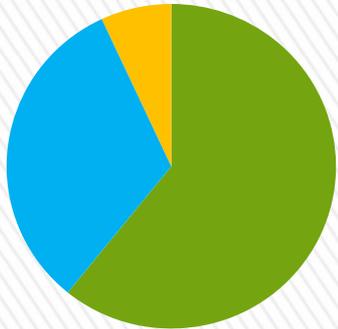


Omitted

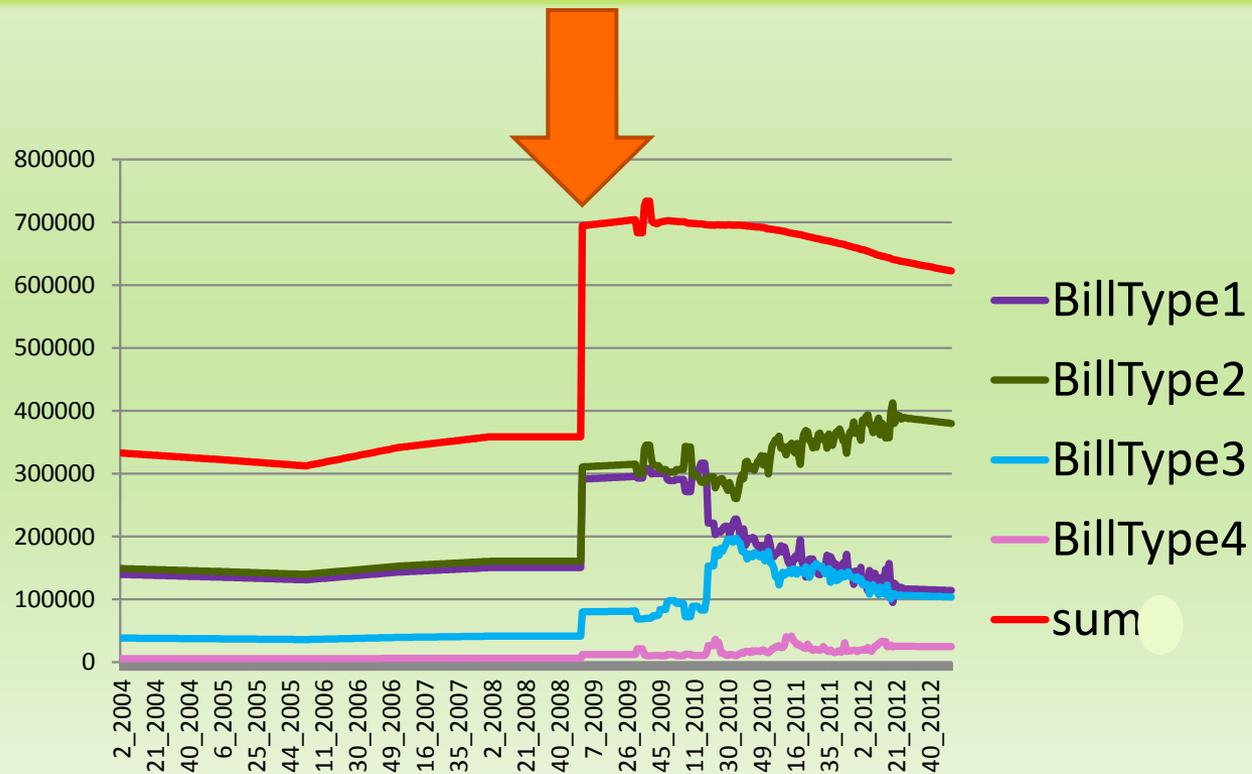
2009



2012



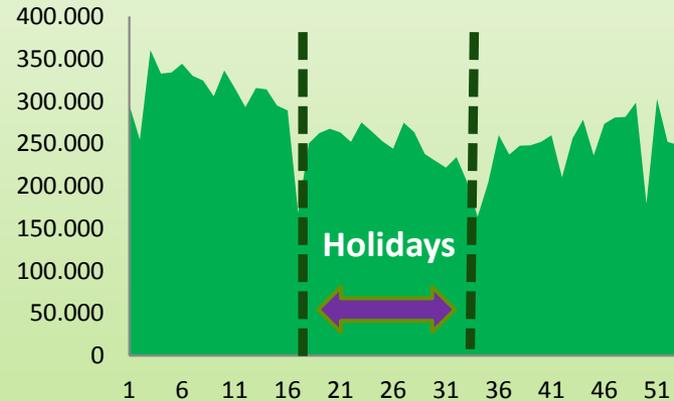
2009: Change due to an European regulation (monthly bills instead of twice-monthly bills).



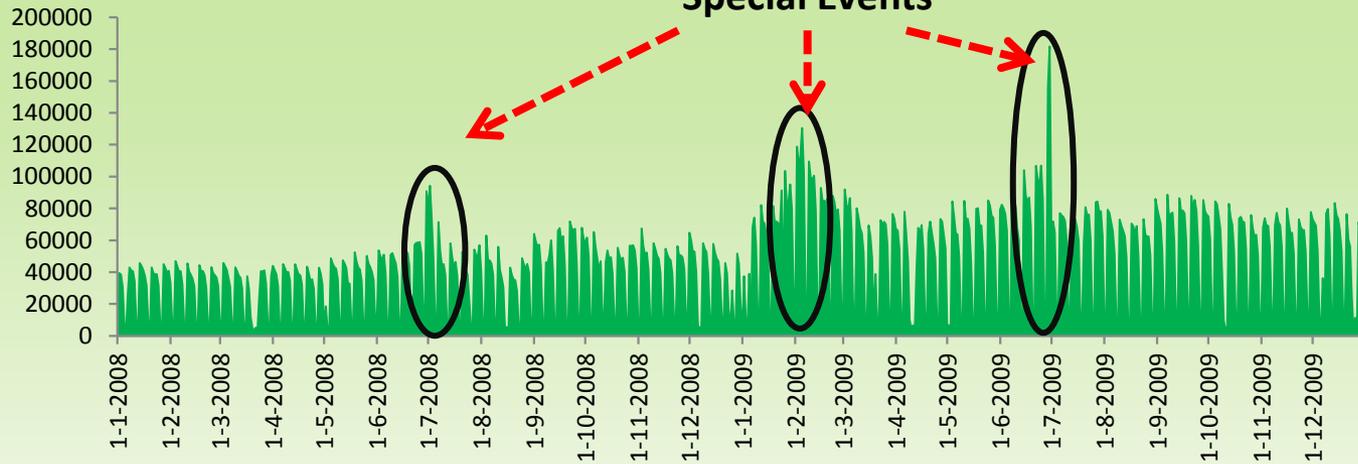
Calls distribution during weeks and holidays



Calls seasonality pattern



Special Events





3. Modelling

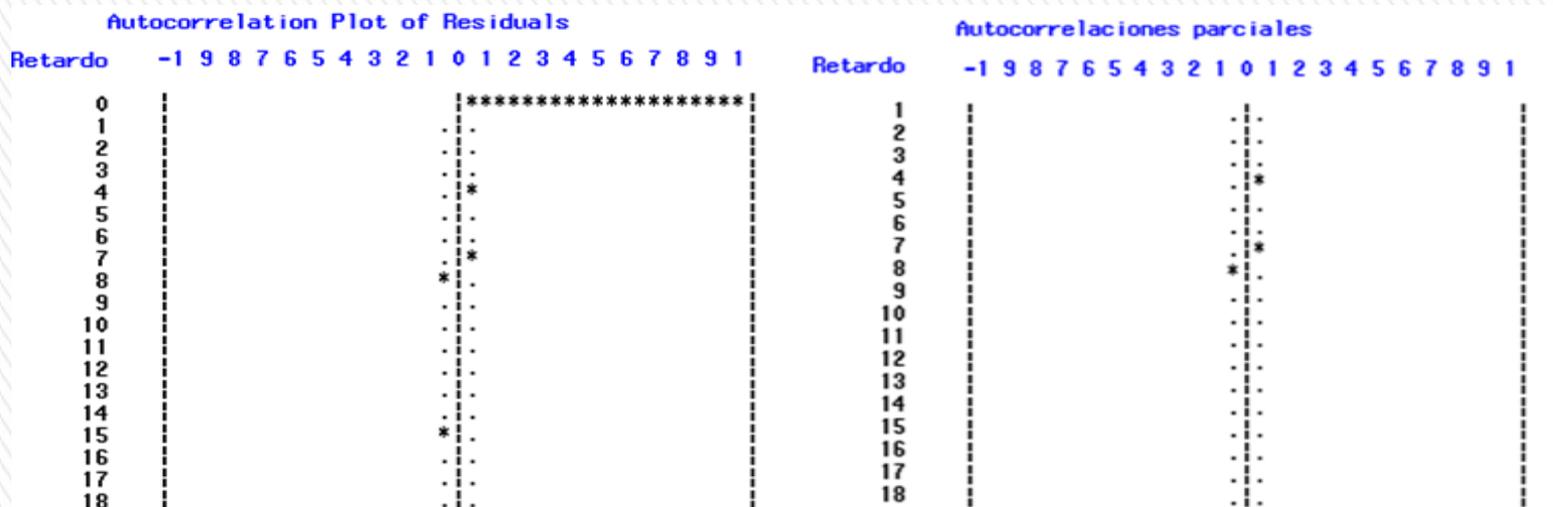
SARIMA Model



SARIMA MODEL (1,1,1)(0,1,1)₇

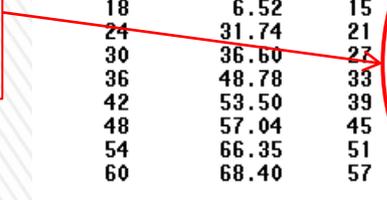
$$\log(\text{calls}_t) = \text{seasonal Inputs} + \eta_t$$

$$\eta_t = \frac{(1 - 0,73L)(1 - 0,64L^7)\hat{\varepsilon}_t}{(1 - 0,38L)(1 - L)(1 - L^7)}$$



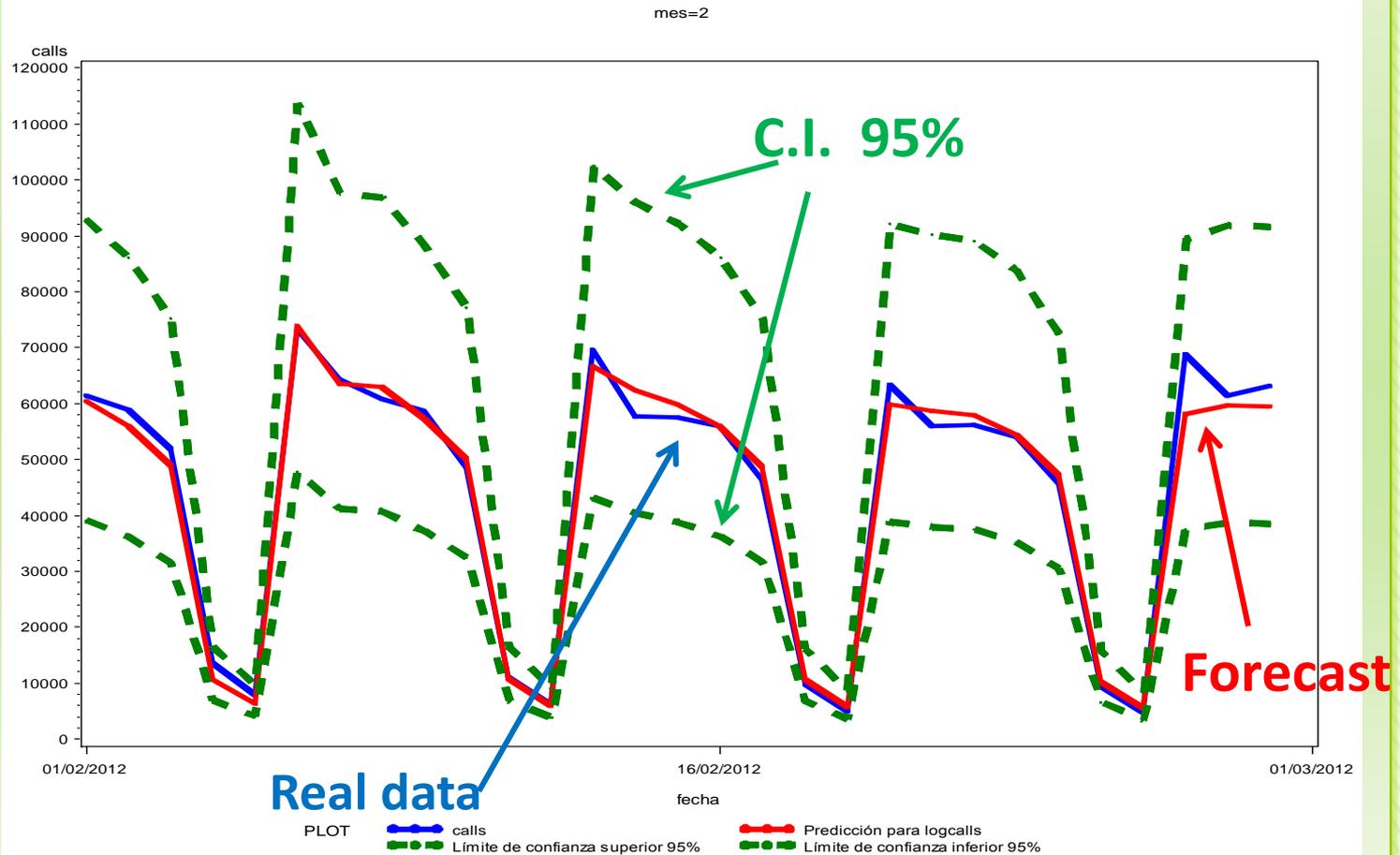
Para retardo	Chi-cuadrado	DF	Pr > ChiSq	-----Autocorre laciones-----					
6	1.87	3	0.5989	-0.010	0.012	0.023	0.031	-0.021	0.003
12	5.48	9	0.7904	0.054	-0.029	0.000	0.004	-0.020	-0.005
18	6.52	15	0.9696	-0.002	-0.007	-0.027	-0.010	0.012	0.013
24	31.74	21	0.0622	-0.136	-0.060	-0.077	0.010	0.009	0.032
30	36.60	27	0.1027	-0.011	-0.023	0.031	-0.016	0.056	0.024
36	48.78	33	0.0377	0.025	0.010	-0.003	-0.060	0.096	-0.015
42	53.50	39	0.0609	0.008	-0.002	0.007	0.047	0.031	-0.046
48	57.04	45	0.1075	0.047	0.023	0.029	0.012	0.013	0.009
54	66.35	51	0.0730	0.031	0.003	0.047	0.043	0.049	-0.054
60	68.40	57	0.1434	0.032	-0.017	0.028	0.011	0.001	-0.005

White noise



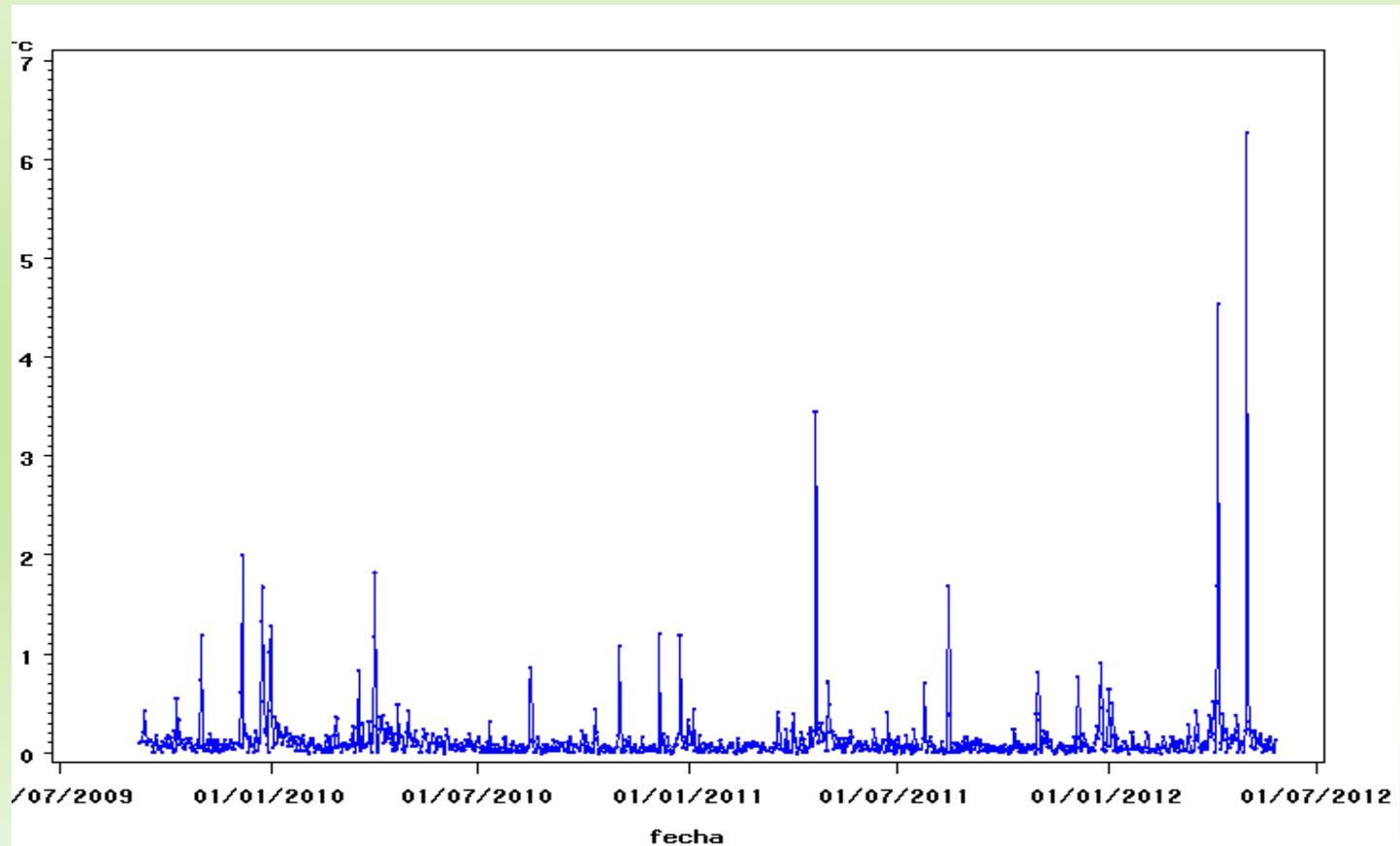


Example of a forecast:

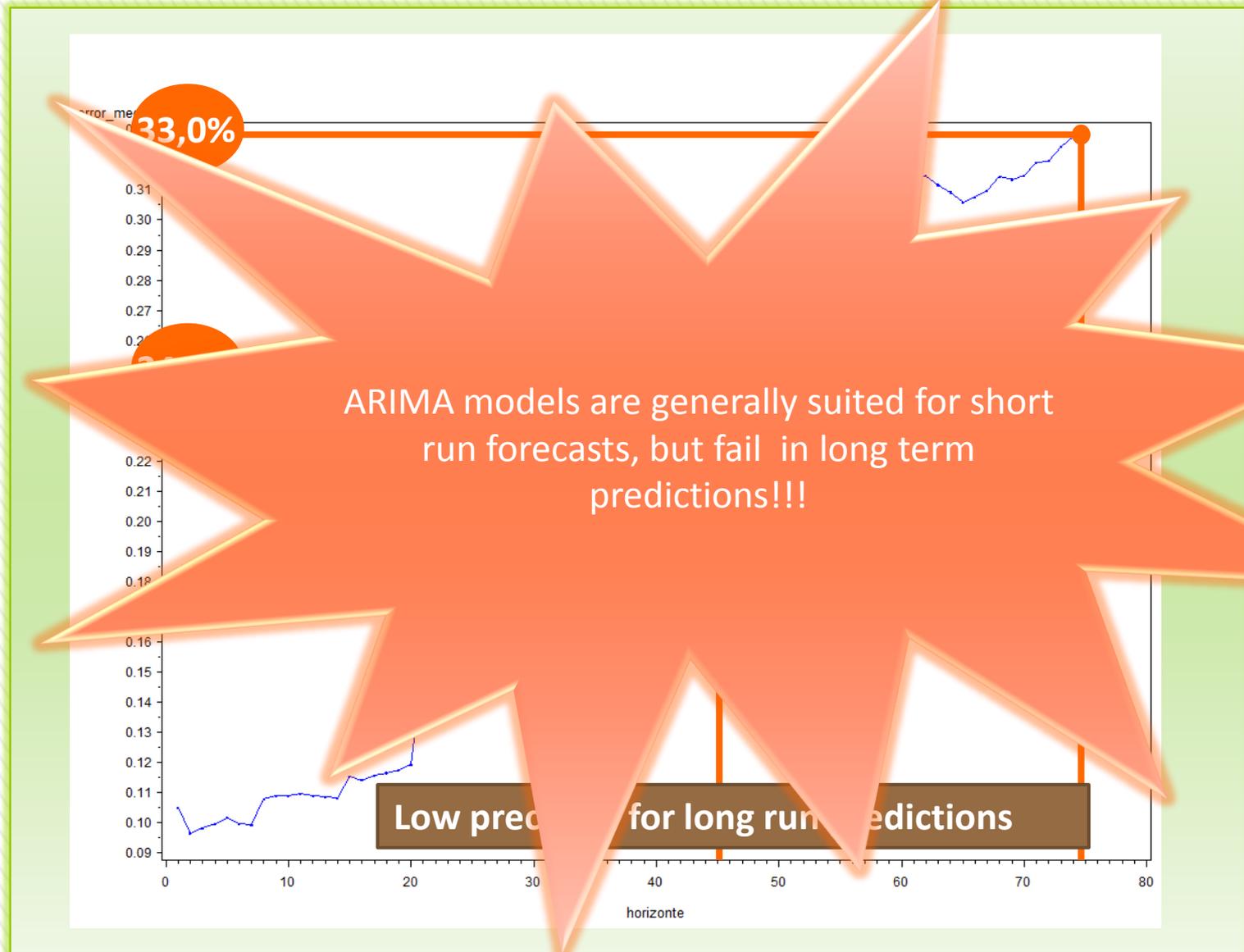




Example of forecast error:



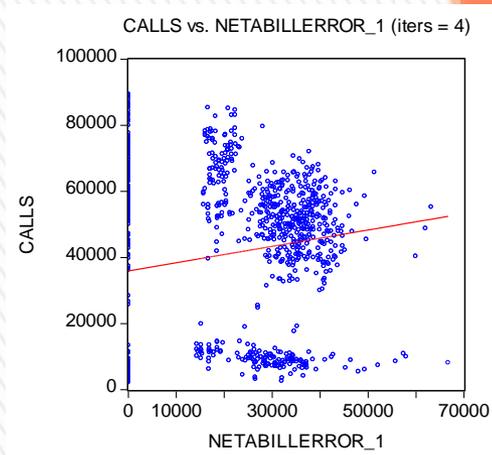
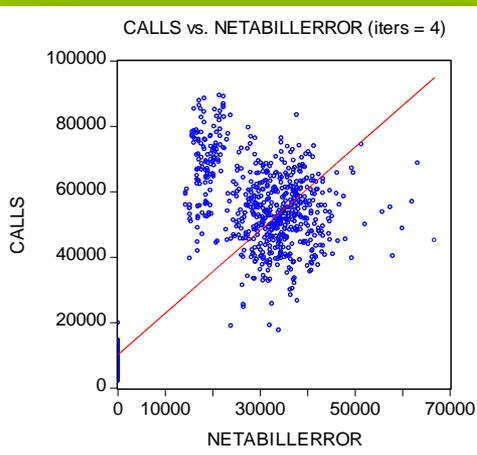
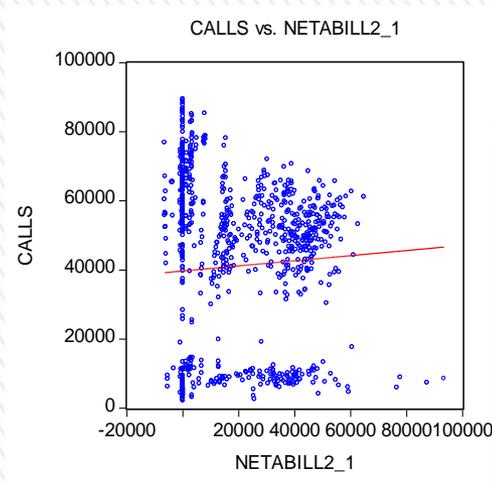
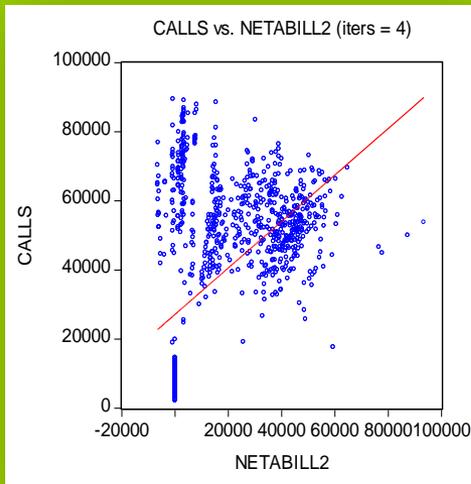
SARIMA Model



A Structural model

- The purpose is to estimate the **relationship** among some **relevant inputs** and the **output**:
 - Using a dynamical model for inputs.
 - Adding some seasonal events.
 - Estimating an additional model for the error term.
- In order to simplify the inputs, we have created two relevant variables:
 - NetBill2: the difference between Billtype2 and Billtype1
 - Neterror: the sum of Billtype3 and Billtype4

➤ We have found strong contemporary relation among target and inputs

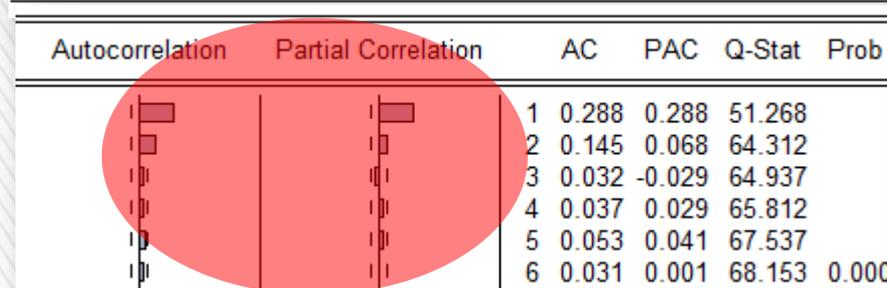
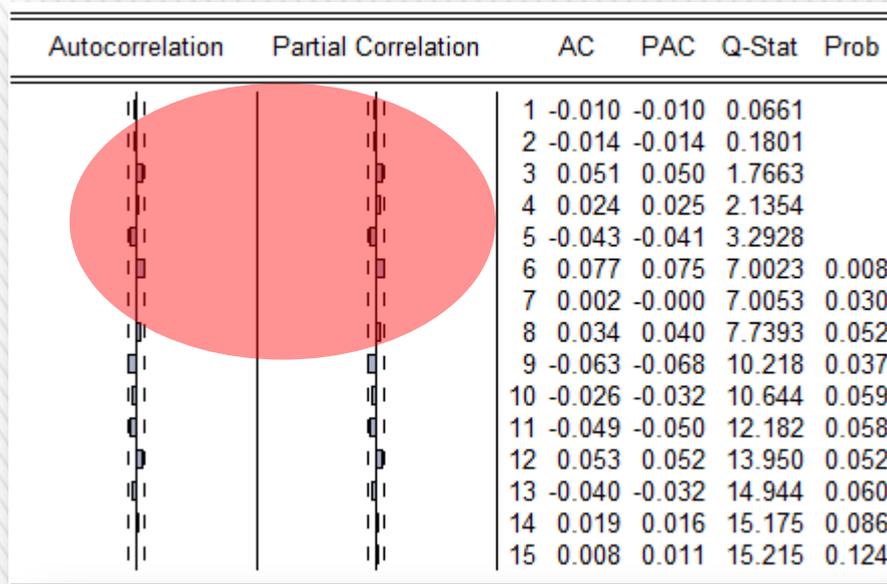


Could be due to
measure errors in
our daily
generation of
weekly inputs.

Structural Model

Variable	Coefficient (lag)	Explanation
$\Delta \log(Calls_t)$		Target variable
$\Delta \log(NetError_t)$	0.20 (0)	An increase of 1% in billtype 3 or 4 increases 0.20% the calls
$\Delta(NetBill2_t)$	-0.285(0) 0.141 (1)	An increase of 1000 billtype 2 over billtype1, decreases 1.4% the calls
Long term seasonality	$-0.0021 \sin\left(\frac{2\pi t}{365}\right) + 0.0010 \cos\left(\frac{2\pi t}{365}\right)$	Is a parsimonious way to take long run cyclical movements
Daily pattern	$0.47\Delta Mon + 0.39\Delta Tue + 0.35\Delta wed + 0.12\Delta fri + 0.0\Delta sat + 0.0\Delta sun$	Dummy variables to catch deterministic daily fluctuations
Error term	$\frac{(1 - 0.36L - 0.54L^2)(1 - 0.20L^7)}{(1 + 0.06L - 0.23L^2)}$	Capturates autocorrelation pattern

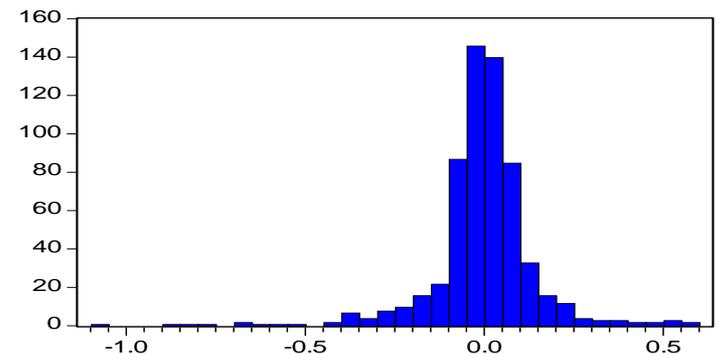
Structural Model



We obtain a white noise residual correlogram...

...however...

...residuals are not normal.
Squared residual correlogram are not white noise

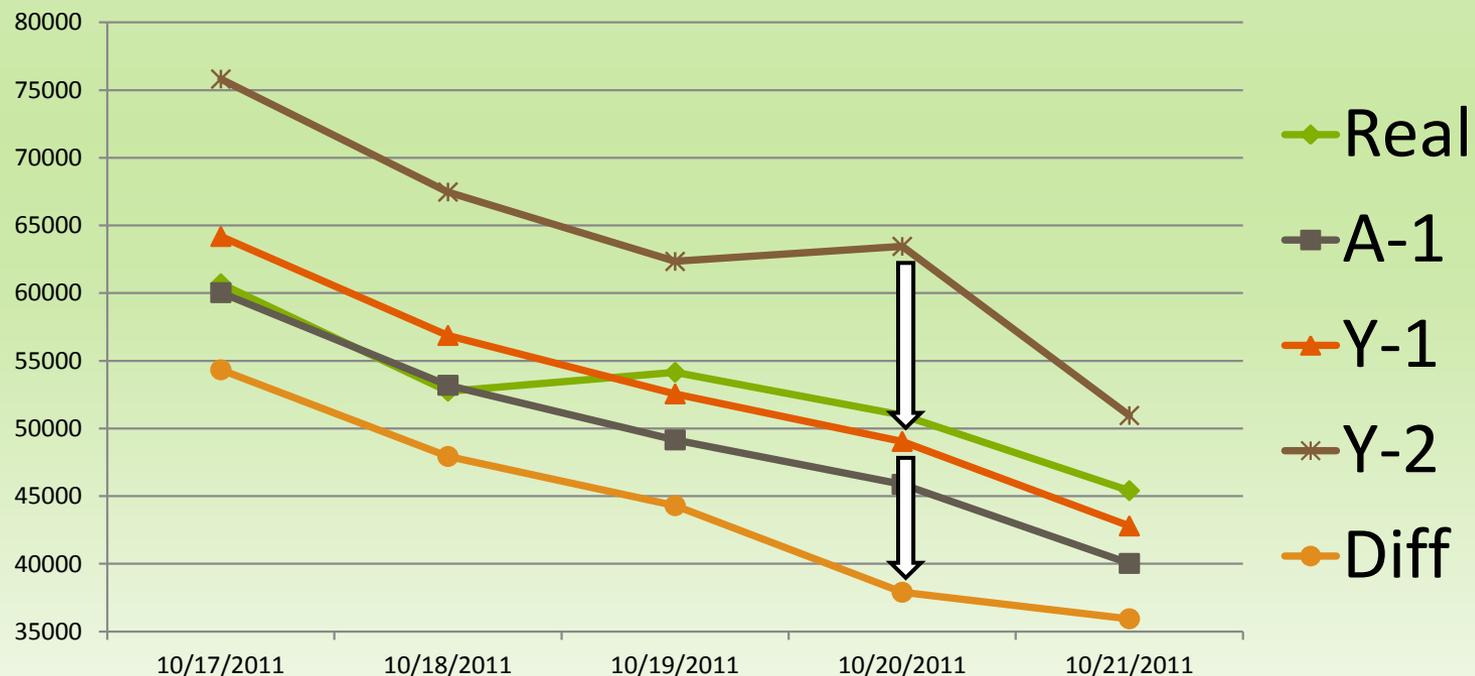


In a next step, we should study the possibility of any GARCH-ARCH structure for error term to model the error volatility.

Some Naïves Models



- Consider the number of calls of previous Year (**Y-1**)
- Adjust the **Y-1** model with a coefficient proportional to the difference with the real data (**A-1**)
- Apply the same variation (%) of the number of calls from Y-1 to Y-0 than from Y-1 to Y-2 (**Diff**)





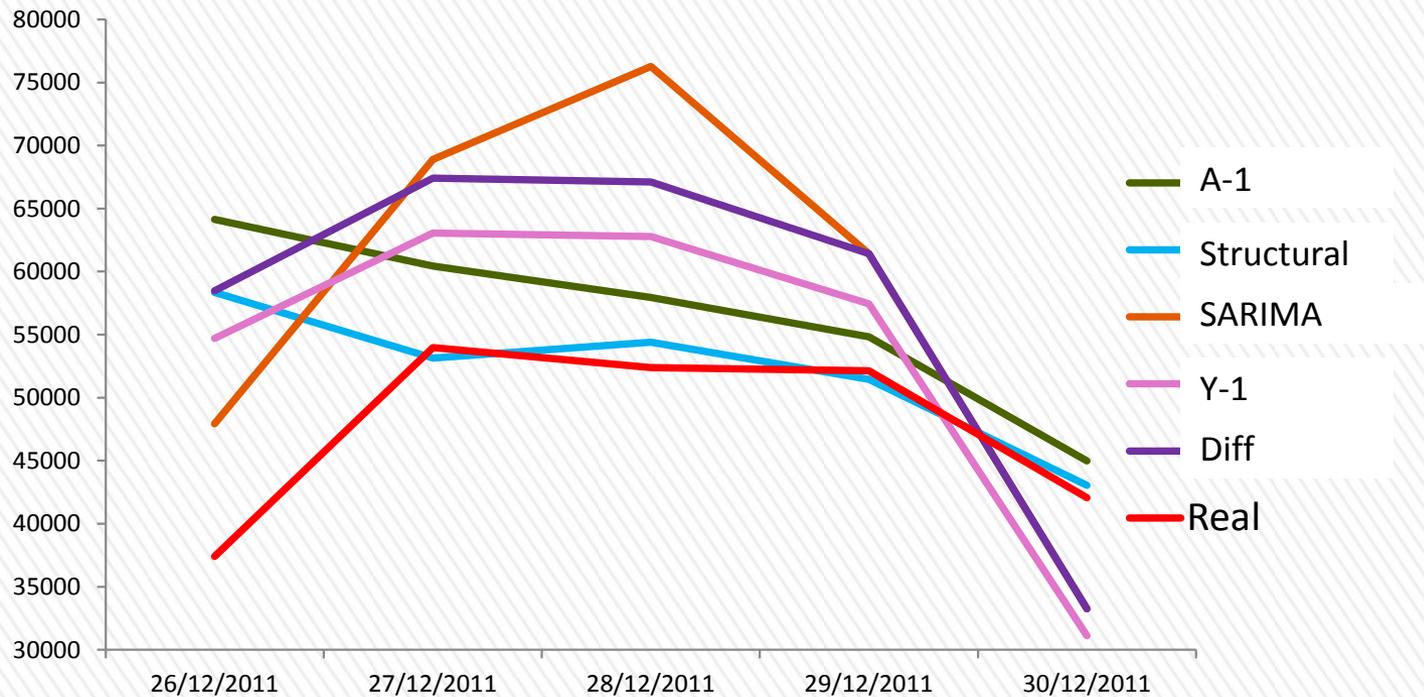
4. Validation and prediction

Validation and prediction



Mean relative error

Structural	SARIMA	Diff	A-1	Y-1
9,31	14,97	12,40	10,32	11,68



Weightened Models

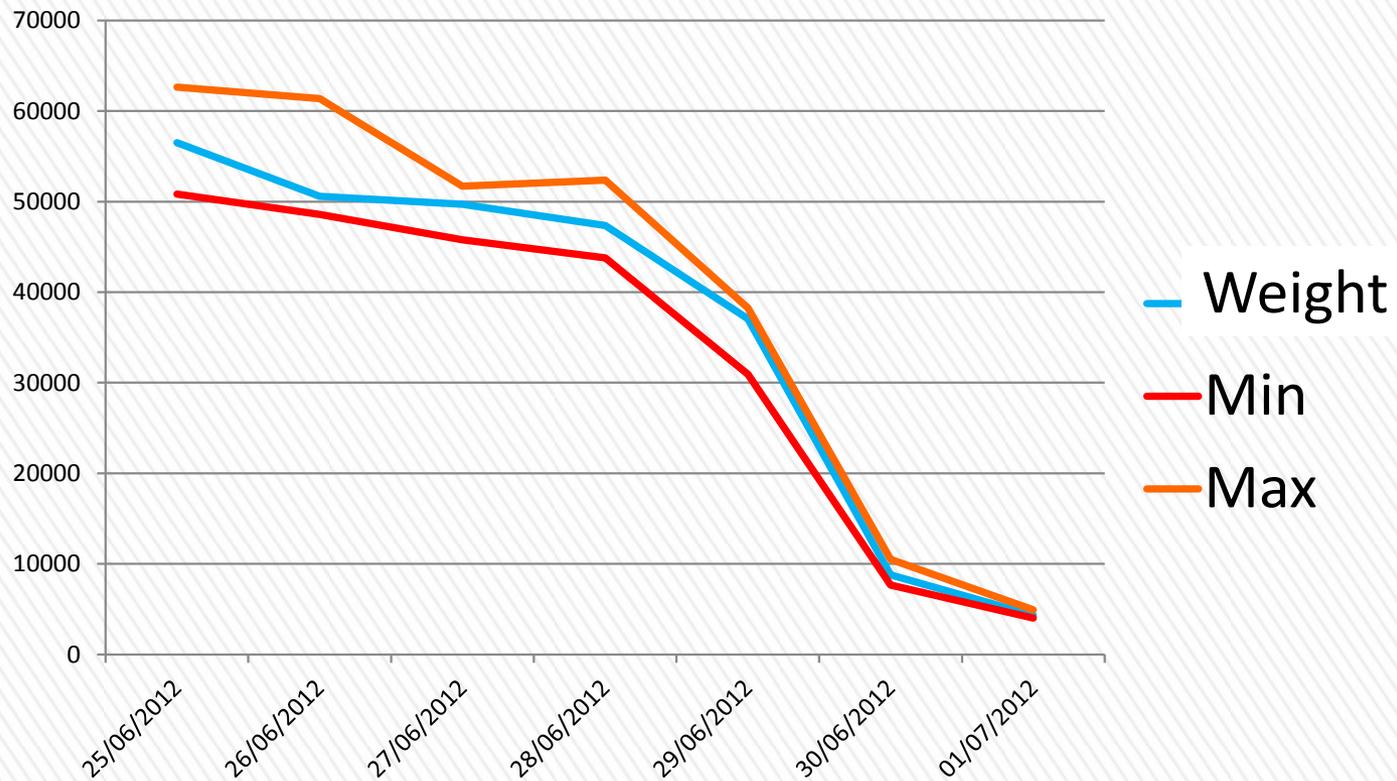
- Following *Clements and Hendry* we have considered a model based on the weights of the solutions generated by all the models (Structural, SARIMA, Differential, A-1).
- We define $J_{\text{err}}(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$ the relative error function which is computed considering the weights $(\alpha_1, \alpha_2, \alpha_3, \alpha_4) \in \Theta = [0, 1]^4$.
- We minimize J_{err} in Θ by considering a Newton method. Then, we obtain:

Structural	SARIMA	Diff	A-1
$\alpha_1 = 0.6$	$\alpha_2 = 0$	$\alpha_3 = 0$	$\alpha_4 = 0.4$

- Mean Error : **8,45** (vs. 9,31 for Structural)

Validation and prediction >>>

We have predicted from 28/05/2012 to 30/12/2012.
For instance, a week obtained from inputs generated by Iberdrola.





5. Conclusions and perspectives



Conclusions

- We have generated models with error values between 8%-15%.
- In addition, we have generated a prediction for future number of calls from an unknown time interval.

Perspectives

- Compare our solution with the real data when available.
- We would like to have additional variables such as campaigns, discretional events, etc.

Thank You!

