



- Predicción de visitas a restaurant
- Caracterización como Serie de Tiempo
- Aplicación de modelos idóneos
- Incorporación de información complementaria

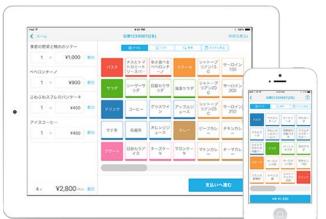




Información disponible





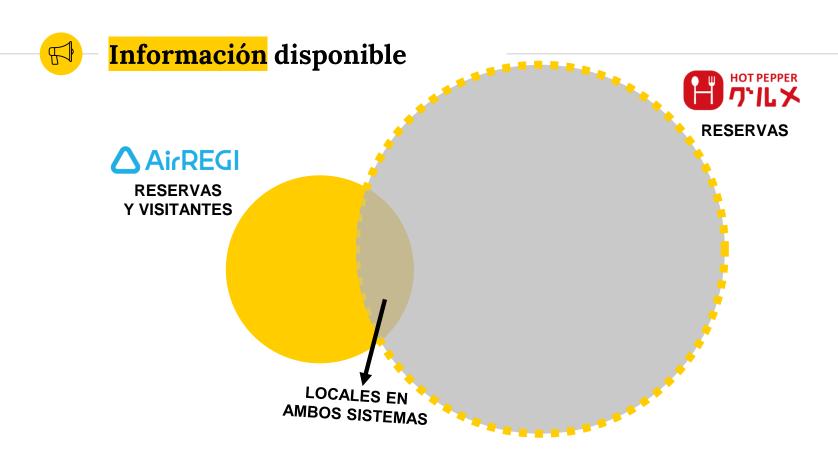






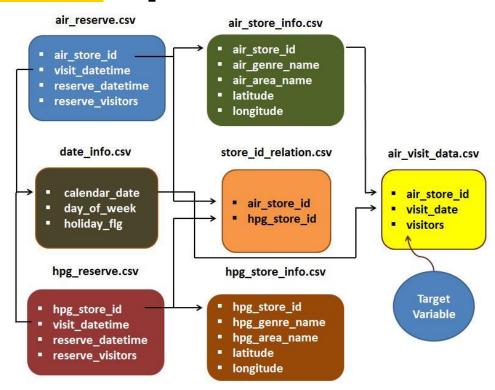


RESERVAS Y VISITANTES

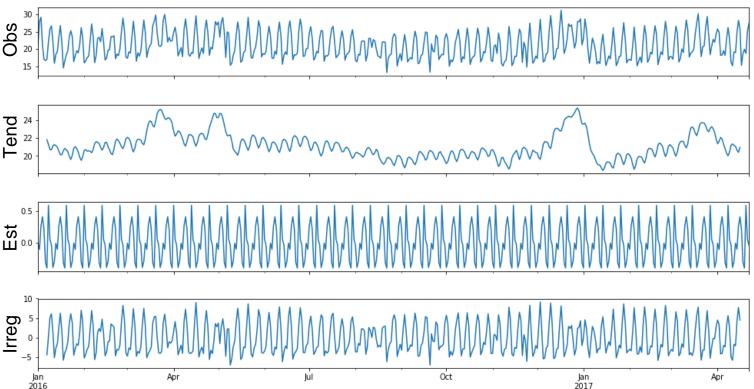




Información disponible









Series de Tiempo

Tendencia

• Incremento/disminución a largo plazo

Estacional

• Serie influenciada por patrones estacionales

Cíclico

Aumento/Caída no propios al período fijo (>2años)

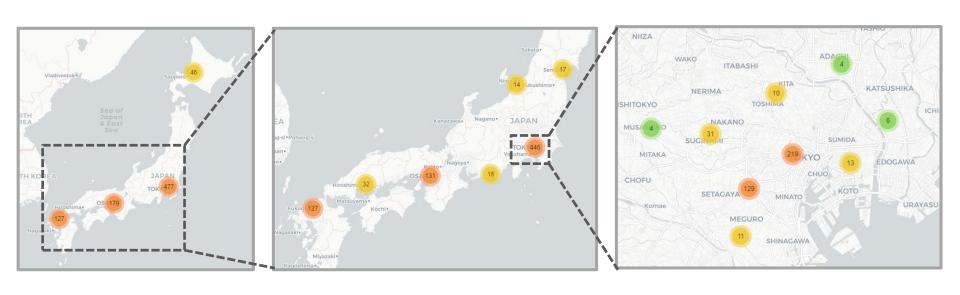
Irregular

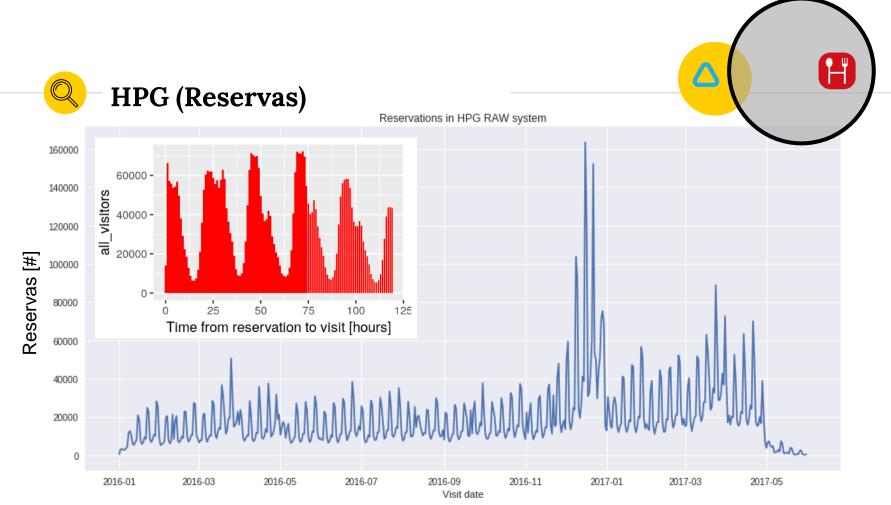
Variaciones aleatorias o residuales

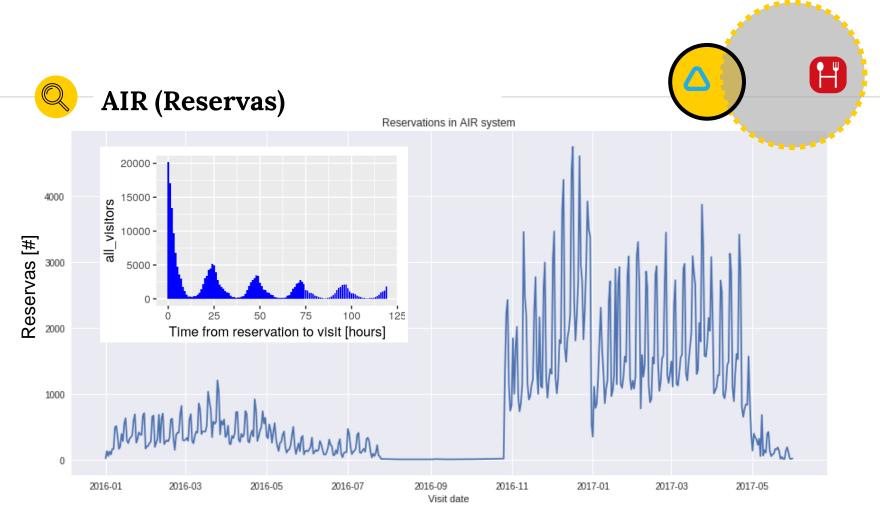


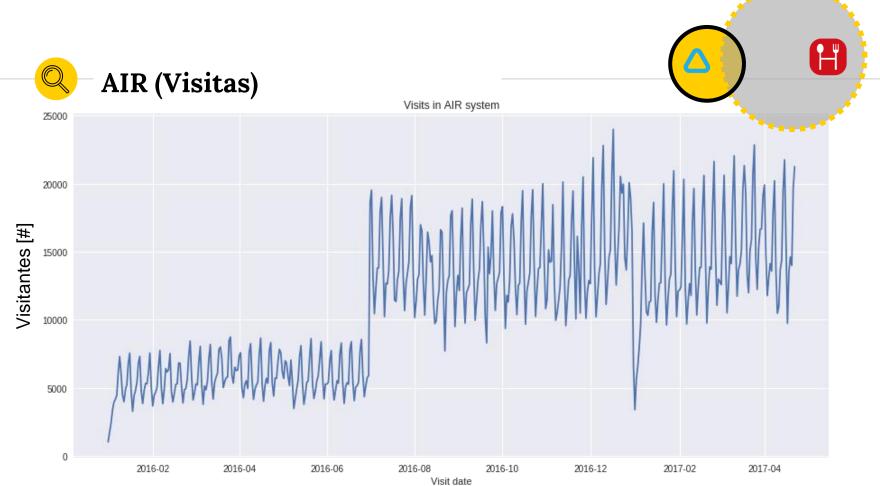


Ubicación de locales





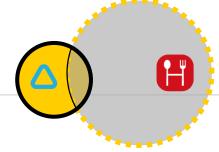


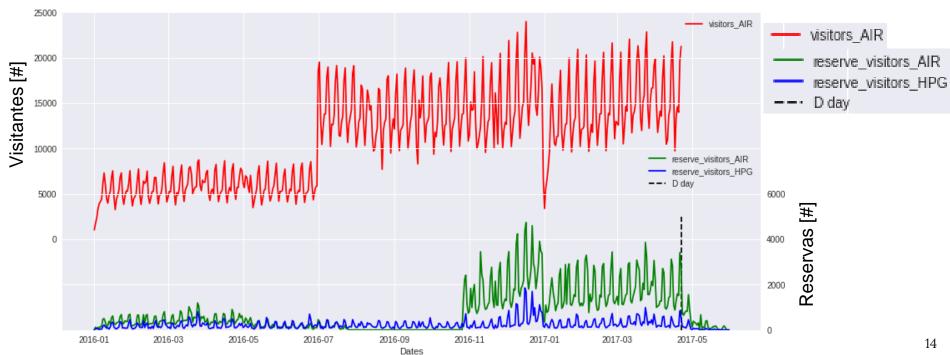




AIR & HPG (Reservas y Visitas)

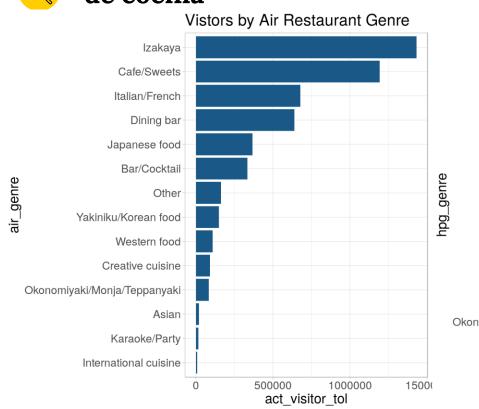
Visitors against reservations in AIR & HPG systems







Tipo de cocina

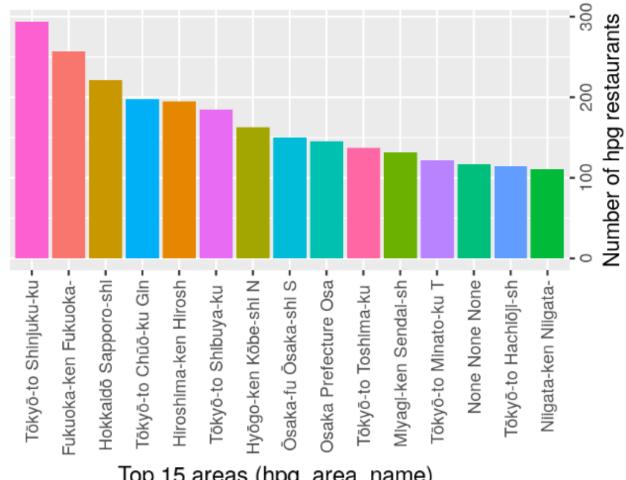


Vistors by HPG Restaurant Genre Japanese style International cuisine Spain Bar/Italian Bar Italian Creation Seafood Grilled meat Japanese food in general Party Steak/Hamburger/Curry Amusement bar Japanese cuisine/Kaiseki Creative Japanese food Okonomiyaki/Monja/Teppanyaki Cafe Karaoke 50000 100000 150000

act_visitor_tol



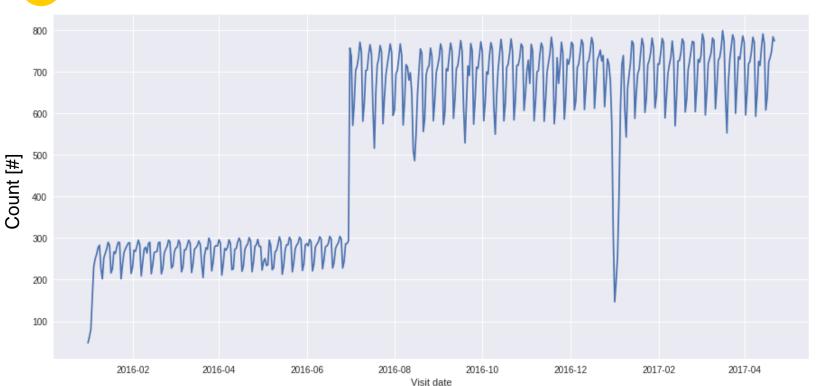
Top Areas (HPG)

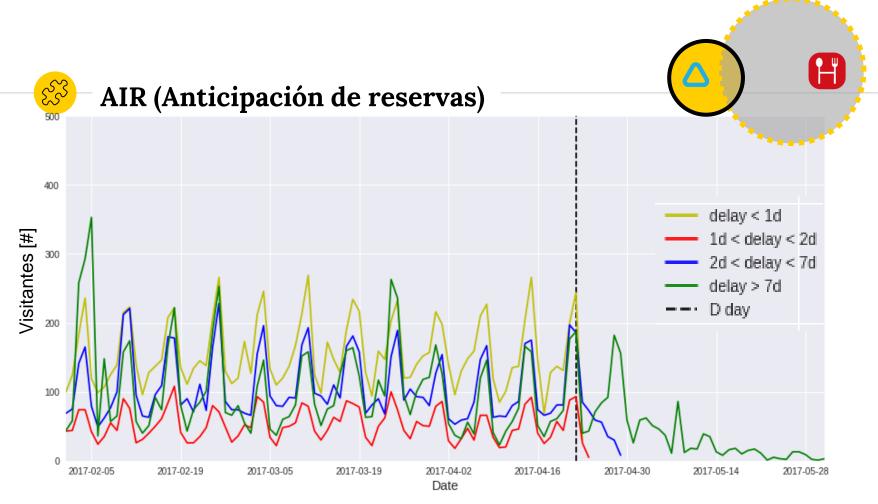


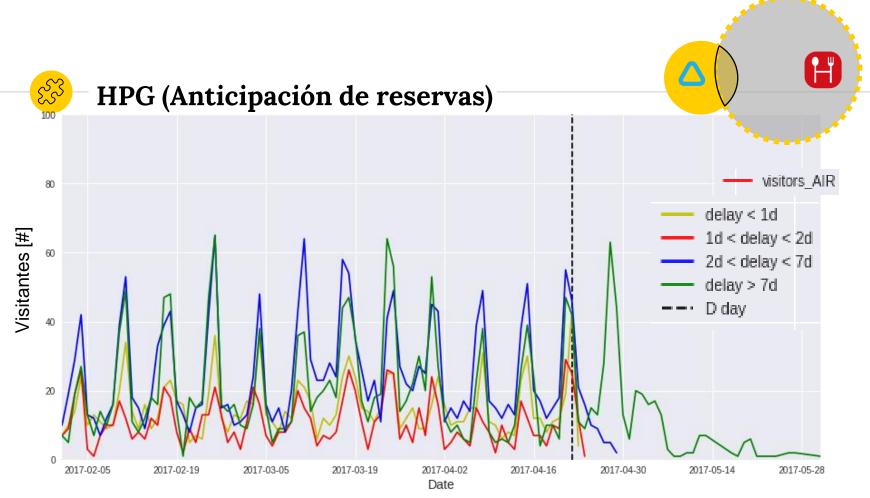




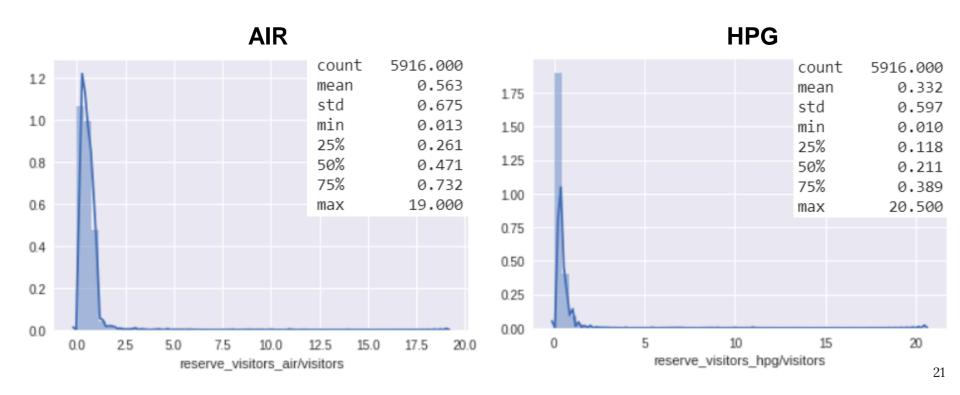
Total de Locales



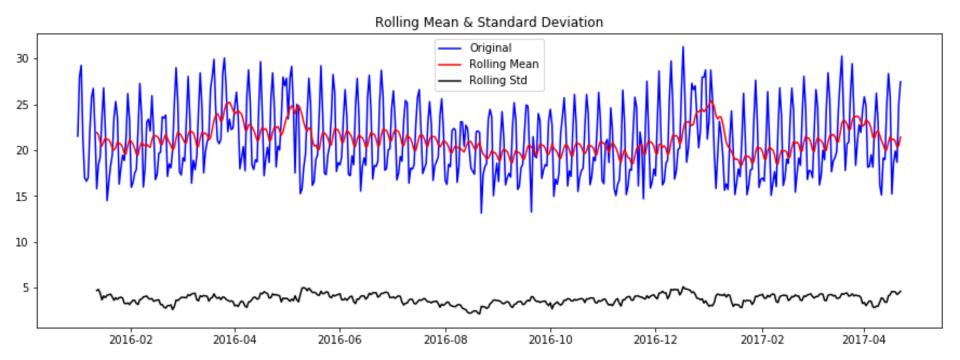




Overbooking



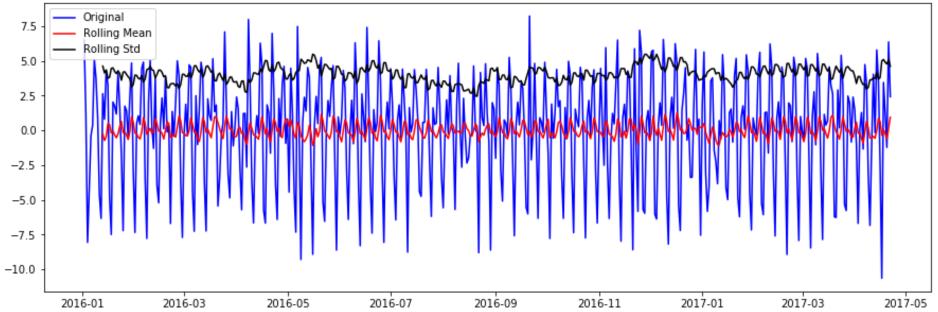
Estacionariedad





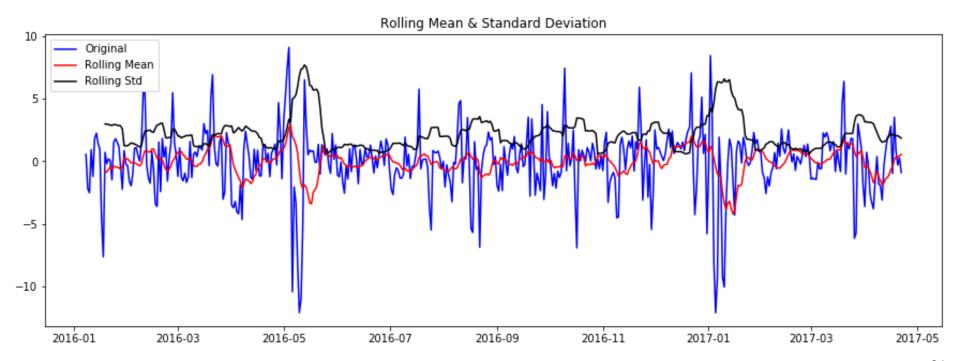
air['visit_mean_diff'] = air.visit_mean - air.visit_mean.shift(1) test_stationarity(air.visit_mean_diff.dropna(inplace=False))





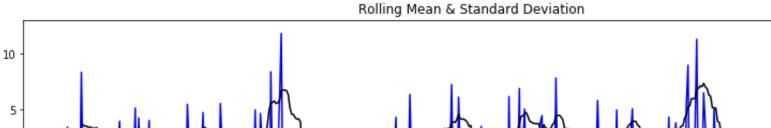


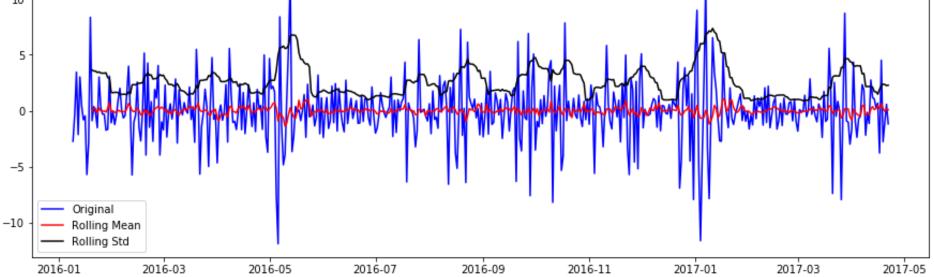
air['visit_mean_seasonal'] = air.visit_mean - air.visit_mean.shift(7)
test_stationarity(air.visit_mean_seasonal.dropna(inplace=False))





air['visit_mean_seasonal_diff'] = air.visit_mean_diff - air.visit_mean_diff.shift(7) test_stationarity(air.visit_mean_seasonal_diff.dropna(inplace=False))

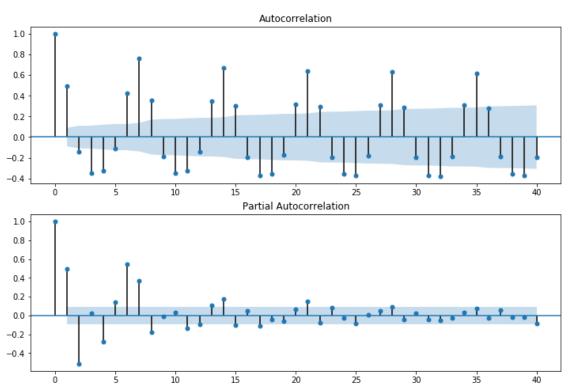






Estacionariedad

fig1 = sm.graphics.tsa.plot_acf(air.visit_mean, lags=40, alpha=.05, ax=ax1) fig2 = sm.graphics.tsa.plot_pacf(air.visit_mean, lags=40, alpha=.05, ax=ax2)





Features adicionales

GENERALES

- Día / Mes / Año
- Feriados
- Cant. Restaurants (x zona)
- Total de locales
- Total reservas (HPG / AIR)
- Clima

PARTICULARES

- Tipo de comida
- Ciudad / Área
- Latitud / Longitud
- Anticipación reservas
 1, 2, 7 o más días

AUTO Regresor

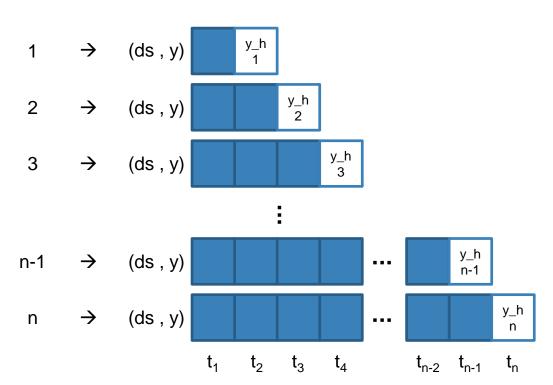
 Predicción de visitas en el corto plazo (1~30 días)

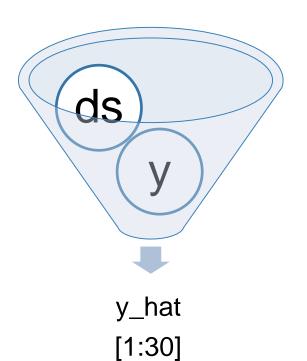






Prophet (facebook)

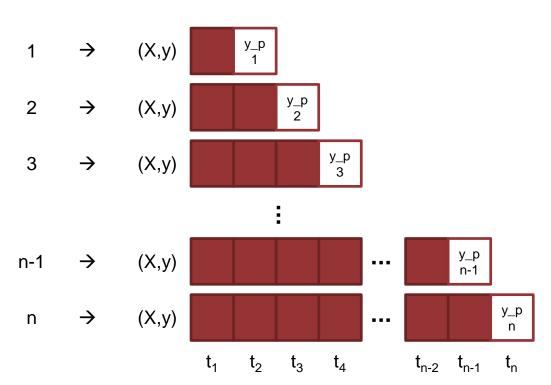


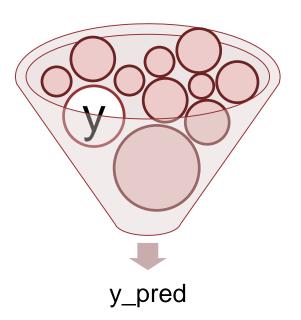




₹<u>Ç</u>

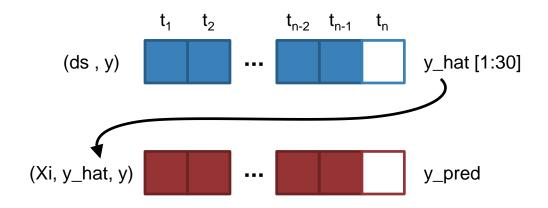
XGBoost (eXtreme Gradient Boosting)

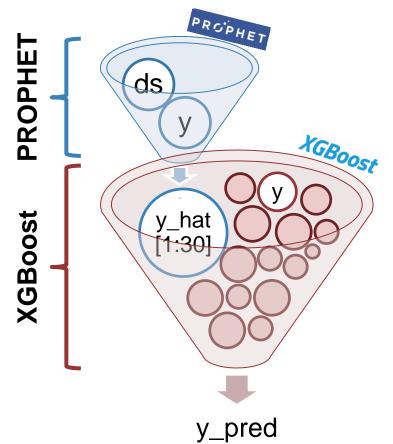


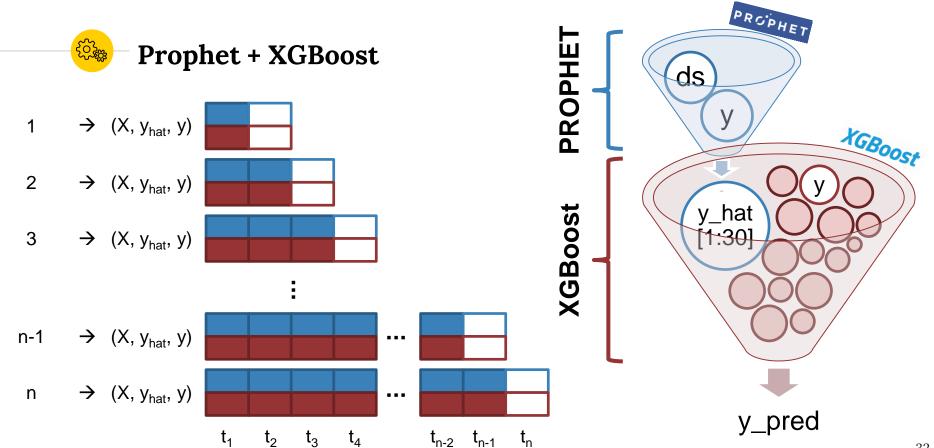




Prophet + XGBoost

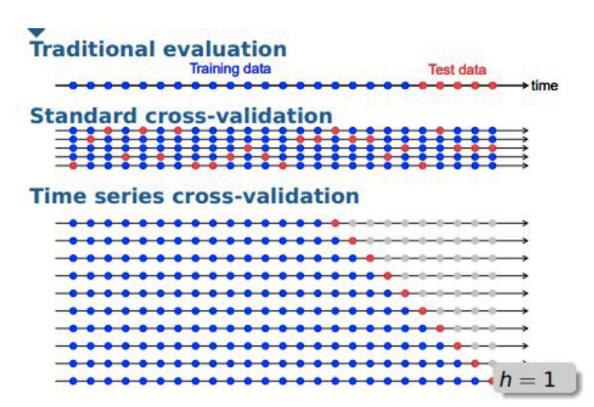






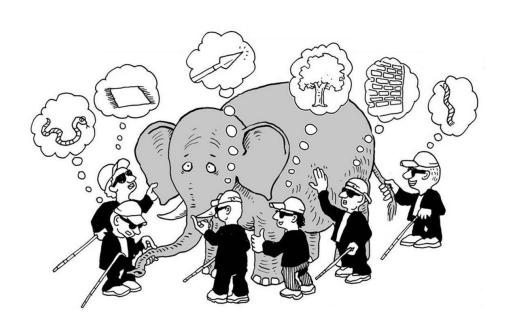


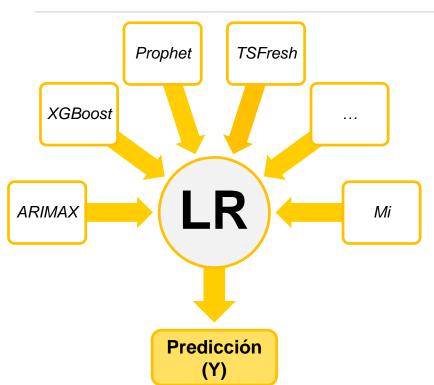
Validación Cruzada





Otro enfoque

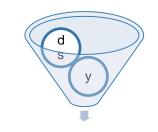


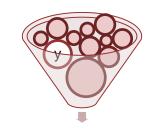


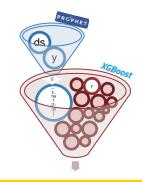


(Score = RMSE)









LOCAL	vis./test	vis./día	Prophet	XGBoost	P+XGB
air_e55abd740f93ecc4	1195	40	18.48	9.47	9.25
air_681f96e6a6595f82	1184	39	16.14	14.47	13.82
air_399904bdb7685ca0	1129	38	15.38	15.93	17.29
air_03963426c9312048	1038	35	26.21	10.30	11.56
air_4cca5666eaf5c709	815	27	6.47	7.35	6.40
air_506fe758114df773	573	19	10.18	9.71	9.51
air_c6ffd6a93e6b68d6	377	12	9.86	5.80	4.68
air_800c02226e2e0288	231	8	4.16	4.04	4.02





Conclusiones

- Múltiples enfoques posibles (modelos)
- Importancia del análisis temporal de los datos (TS)
- Features adicionales propios de la Serie de Tiempo
- Información útil a incluir:
 - "capacidad máxima del local"
 - "reserva concretada o no" (Flag_reserva_caida)
- A partir de eso, se podría estimar:
 - Qué reservas se podrían caer
 - Determinar hasta cuánto hacer overbooking



Aplicaciones múltiples

- Reservas turísticas
 - Hotelería
 - airbnb
 - Excursiones
- Pasajes aéreos
- Turnos médicos
- Espectáculos
- Otros

