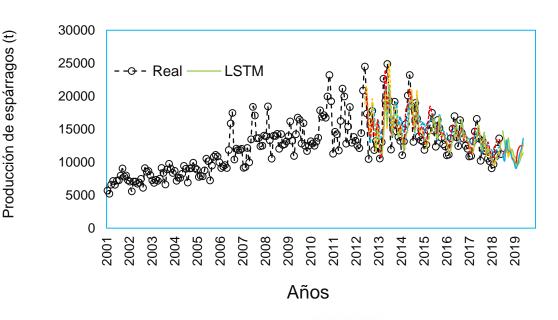






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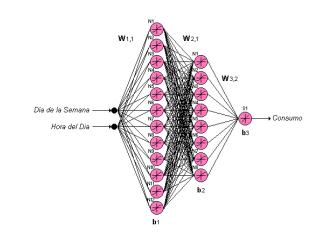




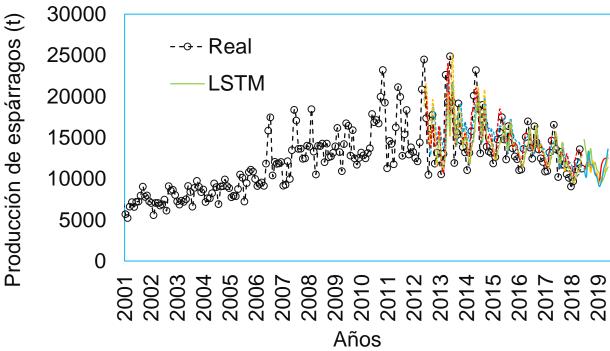
Series temporales con Deep Learning























¿ Quien soy?

Ing. Mg. Jesús Alfredo Obregón Domínguez





Ingeniero en Industrias Alimentarias egresado de la Universidad Privada Antenor Orrego.



Maestro en Ciencias con mención en Estadística Aplicada.



Gerente general



Docente









3





temporales

Series



¿ Quien soy?

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temporales

Series









Learning

Deep

COU

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Series





de la Producción























PONTIFICIA UNIVERSIDAD CATÓLICA DEL PERÚ



















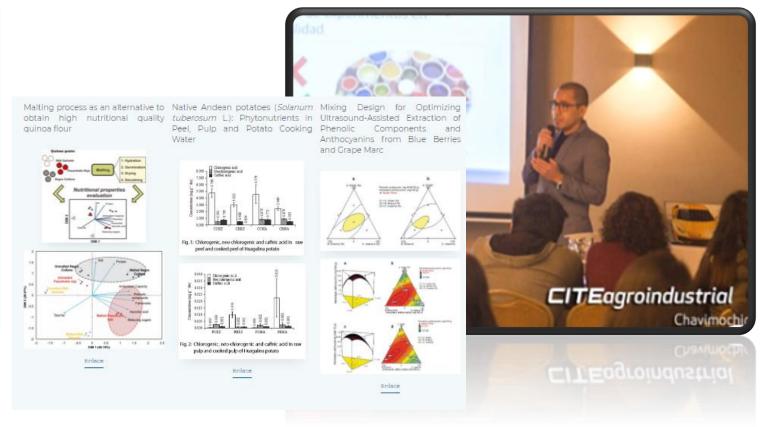




¿ Quien soy?



















Áreas de interés



Learning

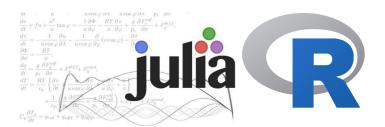
Deep

temporales

Series

- Analítica de datos
- Inteligencia artificial
- Machine learning
- Deep learning
- Estadística deportiva
- Banca y microfinanzas
- **Telecomunicaciones**
- Empresas aseguradoras
- Retail
- Diseño de experimentos
- Bioestadística
- Mercadotecnia
- Mejora continua
- Pruebas sensoriales de alimentos
- Determinación de vida útil
- Enfoque Bayesiano
- Six sigma











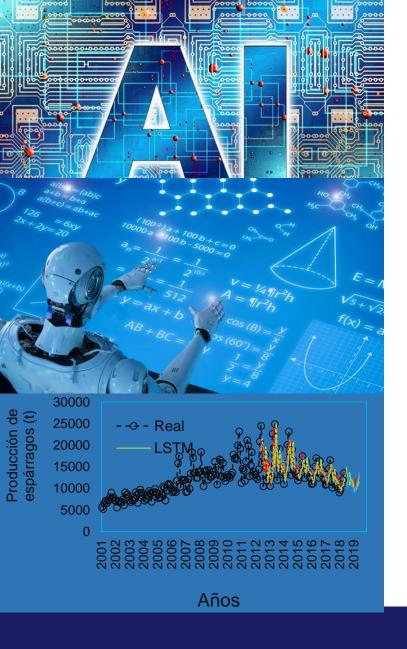














- Evolución de los pronósticos
- ¿Qué es una serie temporal?
- Componentes de una serie temporal
- Series temporales con Machine Learning
- ¿Qué es Deep Learning?
- Redes neuronales recurrentes 6.
- Tipos de redes neuronales recurrentes
- Caso práctico con Python













THE EVOLUTION OF FORECASTING

The combination of Demand Modeling and Machine. Improvements in forecast are most dramatic when there is a fundamental change in the approach to forecasting (from No Forecasting to Naive, from Statutical to Demand Planning and from Demand Planning to Demand Modeling) Learning will decrease errors and lost sales by 33%



| | • | | • | • | * |
|----------------|---|--|---|--|---|
| No Forecasting | Naive Forecasting | Statistical Ferecasting | Demand Planning | Demand Modeling | Machine Learning |
| ERROR CO. | Assumes last year's or last month's domand value will occur again this month 60% | Fits a forecast ourse through flustorical contant quantities Incorporates sessonality, trend data, and moving averages It often done in Excel 50% | Statistically predicts morethly or weekly demand patterns 30% 70% Hierarchy and causal effects are incorporated into the forecast Becomes a nightmare to manage in Excel | Leverages more granular and downstream data to get a cleaner demand signal and reduce vowslity and trulwhip effect Includes techniques that are usually associated with short-term demand sensing to dramatically increase long-term accuracy | Takes advantage of extended and even by data to further increase accuracy Relies on powerful models to consider destand drivers such as promotional details, new product introductions, social media, etc. |













¿Qué es una serie temporal?













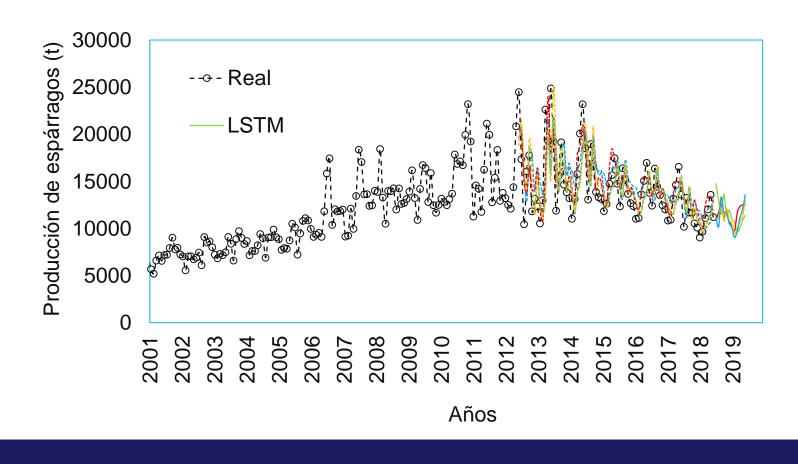








¿Qué es una serie temporal?



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Una serie temporal es una colección de observaciones de una variable tomadas de forma secuencial y ordenada en el tiempo.





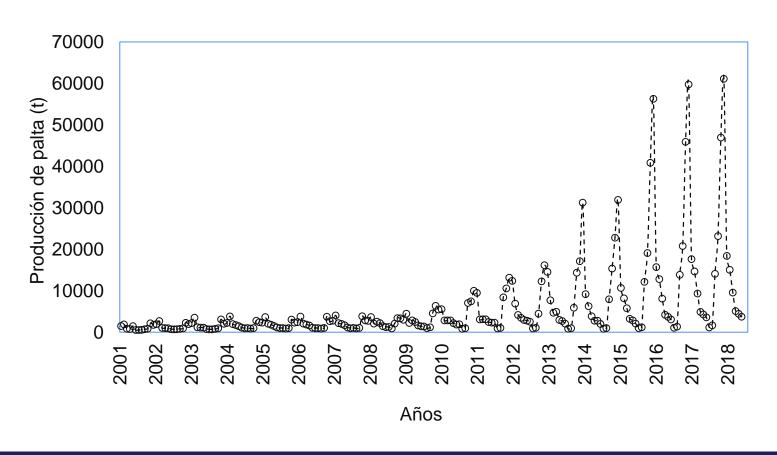






Componentes de una serie temporal





- 1. Tendencia
- 2. Estacionalidad
- 3. Ciclo
- 4. Aleatorio/Irregular







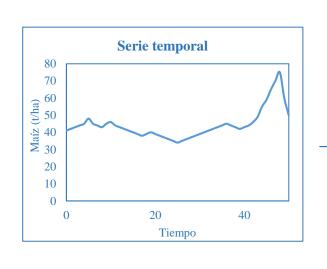


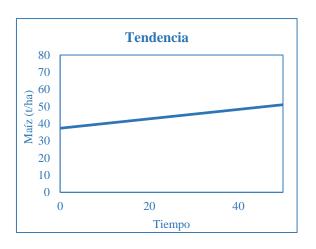


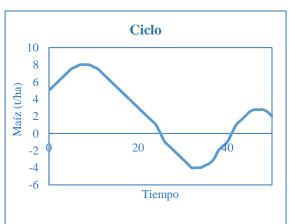


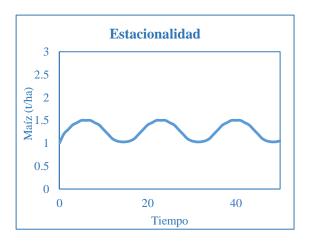
Componentes de una serie temporal

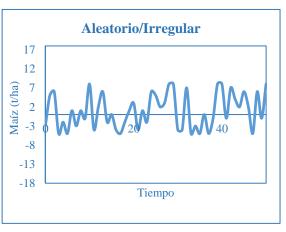




















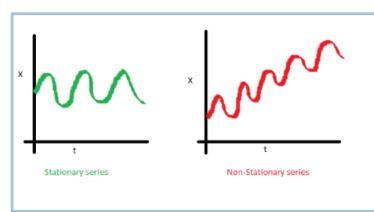


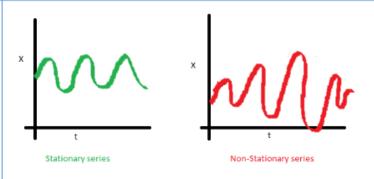


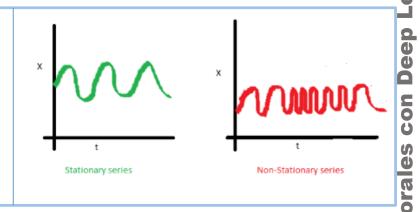
Tipos de series temporales



Media **Varianza** Covarianza







La media de la serie no debería estar en función al tiempo. La gráfica en rojo es estacionaria por que incrementa al transcurrir el tiempo.

La varianza de la serie no debería estar en función al tiempo. Esta propiedad conocida como La gráfica en homoscedasticidad. rojo es no estacionaria por que la distribución de los datos es variable a lo largo del tiempo.

La covarianza del *i th* termino y el (*i* + m)th termino no debería estar en función del tiempo. La gráfica en rojo es no estacionaria por que la distribución se acorta cuando el tiempo transcurre, incluso la covarianza no es constante en el tiempo.







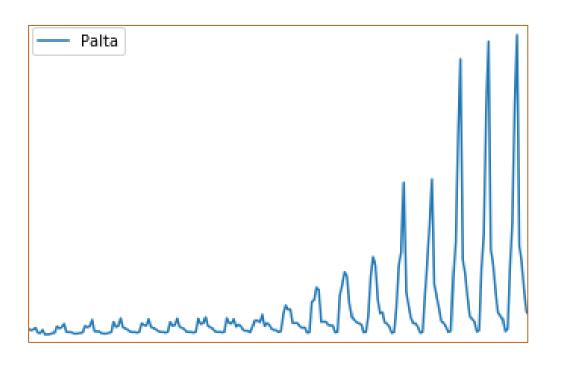




Series temporales según cuantas variables se observan

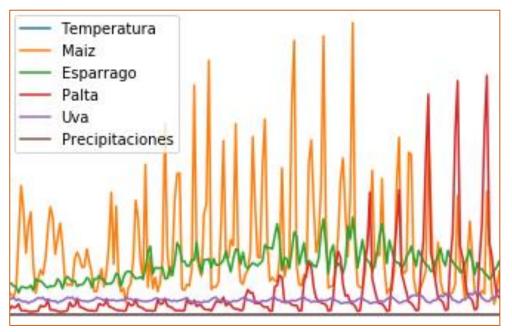


Univariadas



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Multivariadas









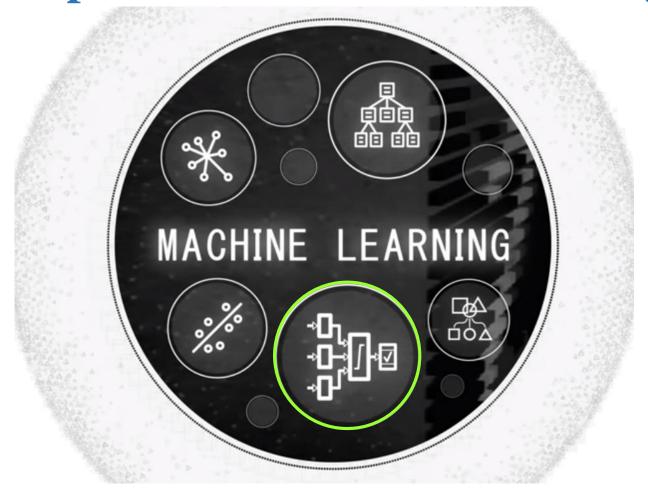






Series temporales con machine learning















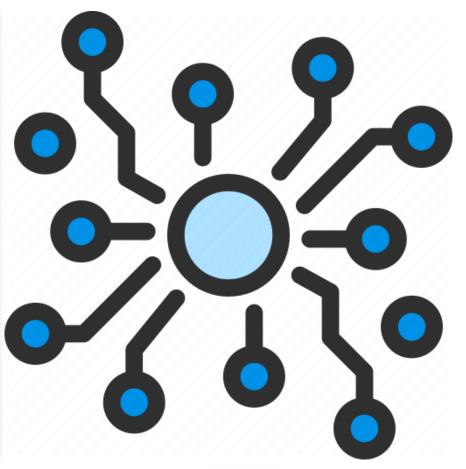




Redes neuronales artificiales













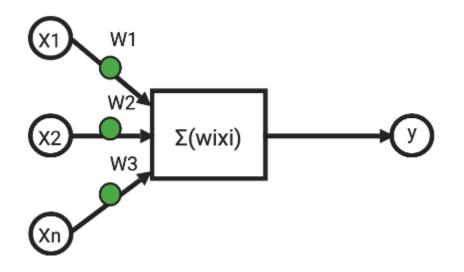


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¿Qué es una neurona artificial?











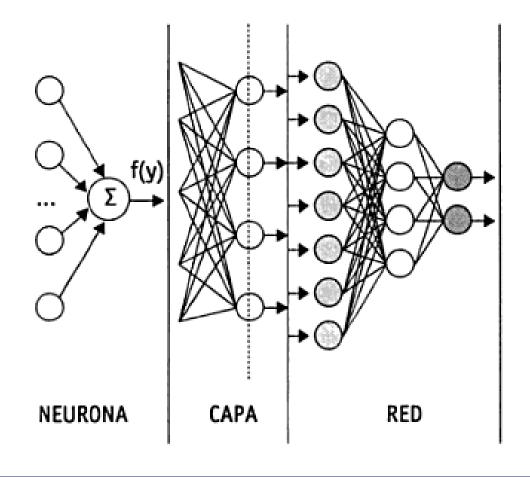






¿Cómo funciona la neurona artificial?

















¿Qué es deep learning?

















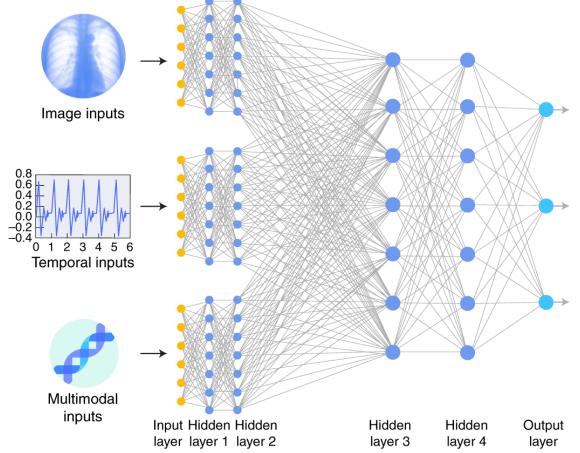


¿Qué es Deep Learning?















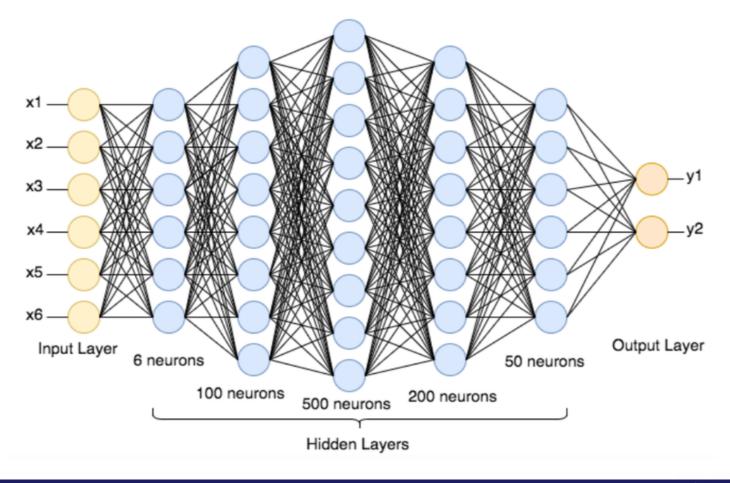






¿Qué es deep learning?











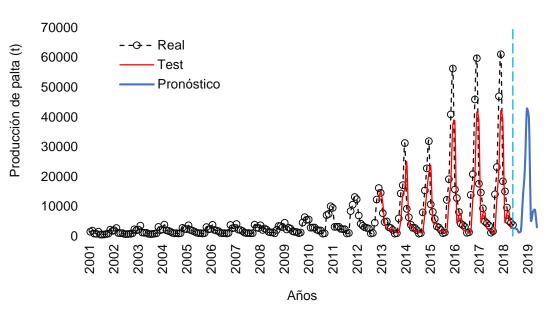


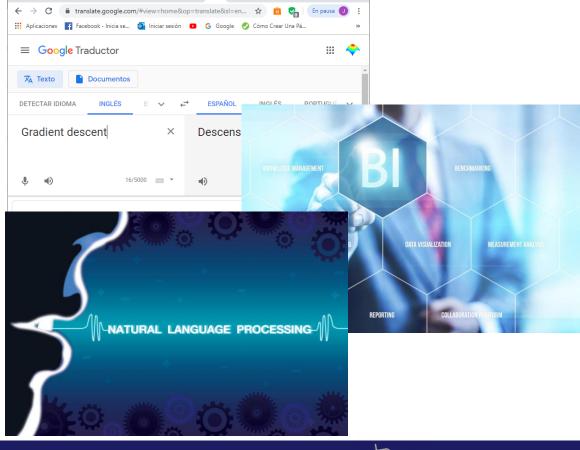




Redes neuronales recurrentes (RNN)















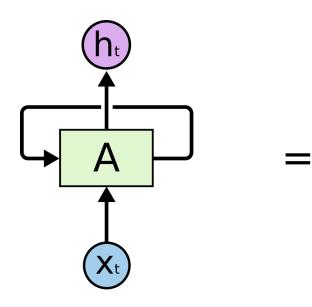


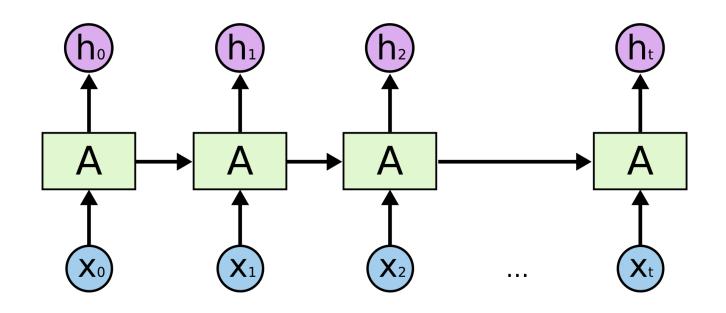
Series temporales con



Redes neuronales recurrentes (RNN)



















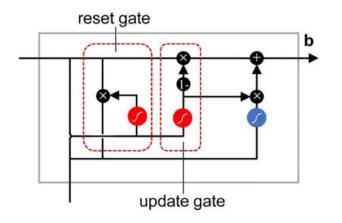
Tipos de redes neuronales recurrentes

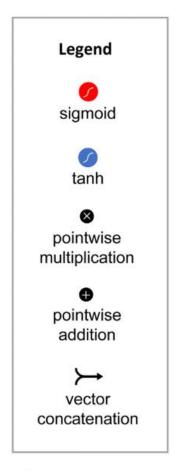


(RNN)

LSTM (Long Short Term memory)

forget gate cell state input gate output gate





GRU (Gated Recurret Unit)







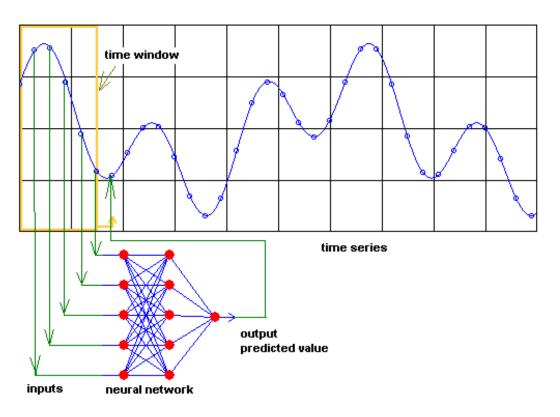






Ventana deslizante (sliding window method)













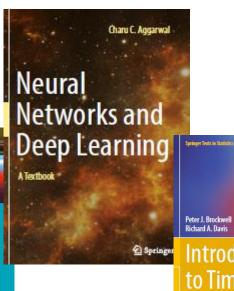


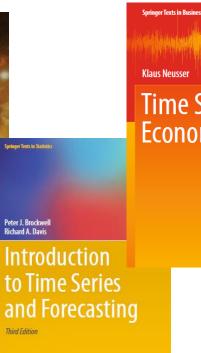


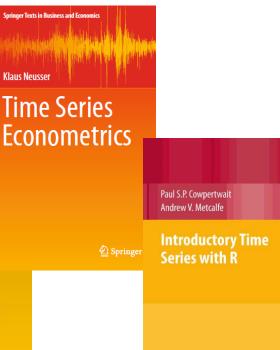
Como aprender?

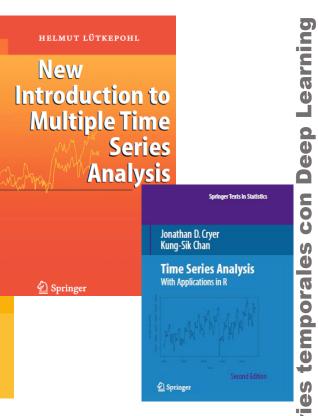


















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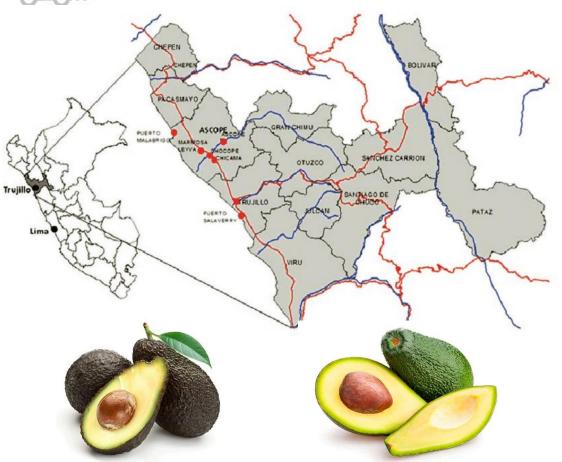


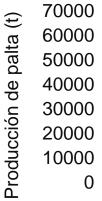


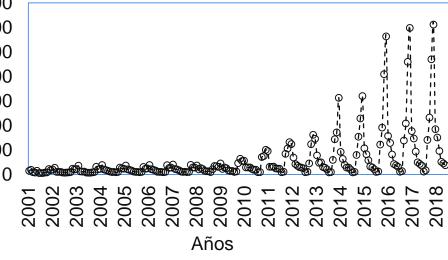


Caso práctico













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