Agrupamiento no supervisado de series de tiempo epidemiológicas de México entre 2005 y 2015

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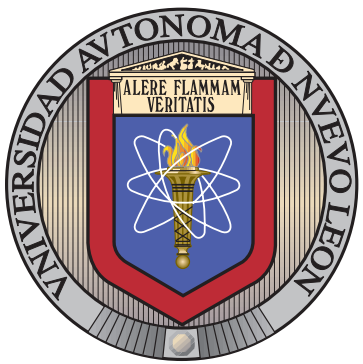
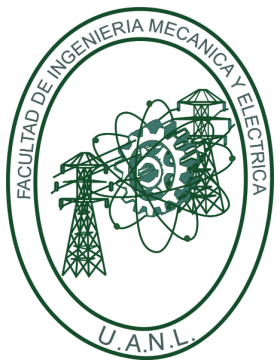




Contenido

Conceptos fundamentales

Semana epidemiológica

- Estándar médico de medición temporal [1]
- Primera semana epidemiológica termina el primer sábado de enero

CIE

- Clasificación Internacional de Enfermedades [44]
- Organización Mundial de la Salud
- Actualmente en la versión 11; periodo 2005-2015, versión 10

Hipótesis

La agrupación a partir de las características de las series de tiempo de los registros semanales de morbilidad en México publicados entre 2005 y 2015 ofrece información estadísticamente significativa que permite **asociar** dichas series de tiempo con una clasificación de referencia con que se etiqueta cada enfermedad.

Objetivos

- Extraer y preparar datos
- Obtener características de las series de tiempo
- Agrupar datos caracterizados
- **Comparar grupos generados con la CIE asignada por la OMS**
- Describir los grupos generados

Metodologías estadísticas

- **Estadística**
  - Descriptiva
    - Medidas de tendencia central
    - Medidas de dispersión
  - **Inferencial**
    - Supervisada
    - **No supervisada**

Algoritmos de agrupamiento para series de tiempo (1979 a 2017)

		Artículos
Métodos	***k*-medias**	[3, 4, 7, 12, 16, 20, 22, 23, 28, 29, 34]
	DTW	[17, 21, 27, 49]
	ARMA	[4, 45, 46]
	ARIMA	[8, 19]
	Jerárquico	[35, 49]
	Red compleja	[13]
Entrada	**ACF**	[3, 11, 12, 43]
	Wavelets	[23, 41, 48]

Origen

1. Descarga iterativa de `PDF`s por patrones en `URL`, p. ej.: `http://www.epidemiologia.salud.gob.mx/doctos/boletin/2008_sem25.pdf`
2. Descarga manual (2013)
3. Descarga de páginas `JPG` comprimidas en `ZIP` (2011)
4. Creación de documento `PDF` con `PDF Mergy` [42] a partir de `JPG`s (2011)

CUADRO 5.1 *Casos por entidad federativa de* ***Enfermedades Infecciosas*** *del Aparato Respiratorio hasta la semana epidemiológica 5; Influenza hasta la 6 del 2012*

ENTIDAD FEDERATIVA	Neumonías y Bronconeumonías CIE-10ª REV. J12-J18 excepto J18.2				Influenza (A H1N1) CIE-10ª REV. J09			Influenza Estacional CIE-10ª REV. J10-J11		
	2012			2011	2012			2012		2011
	Sem.	Acum.		Acum.	Sem.	Acum.		Acum.		Acum.
		M	F			M	F	M	F	
Aguascalientes	79	170	233	677	17	27	19	1	1	5
Baja California	161	445	434	909	18	17	13	6	11	3
Baja California Sur	36	98	91	176	30	74	67	8	8	-
Campeche	20	50	48	86	8	11	16	-	3	-
Coahuila	65	232	217	692	7	10	5	-	-	-
Colima	48	100	111	207	30	50	69	1	1	6
Chiapas	73	160	179	343	21	60	78	9	7	1
Chihuahua	246	654	695	1 632	19	10	18	-	-	6
Distrito Federal	180	806	779	2 154	34	226	282	13	21	65
Durango	69	205	227	625	21	16	14	1	-	-
Guanajuato	184	414	425	1 105	19	22	27	1	1	-
Guerrero	98	210	194	417	9	20	21	2	1	3

Extracción

para cada *directorio en año* **hacer**
- **para cada** *archivo en directorio* **hacer**
  - **si** *termina con* `.pdf` **entonces**
    - leer páginas con `PyPDF2` [31];
    - **para cada** *página en archivo* **hacer**
      - **si** *contiene cuadro de interés* **entonces**
        - extraer contenido con `tabulapy` [2];
        - extraer posiciones del contenido en `JSON`;
        - seleccionar pixeles de columnas de interés;
        - **para cada** *columna en página* **hacer**
          - ajustar anchos de columna;
          - leer filas;
        - **fin**
      - **fin**
    - **fin**
  - **fin**
  - exportar datos en `CSV`;

fin

Resultado

```
2006|02|Tabasco| 'Paratifoidea\r y otras
salmonelosis\rCIE-10a REV.\rA01.1-A02'| '121'
```

784 660 registros

Limpieza

```
for i in range(len(lines)):
  lines[i][1] = lines[i][1][-2:]

  lines[i][4] = str(lines[i][4])
  lines[i][4] = lines[i][4].replace("'", "")
  lines[i][4] = re.sub("^\s+", "", lines[i][4])
  if lines[i][4][0] is "-":
    lines[i][4] = "0"
  if " " in lines[i][4]:
    lines[i][4] = lines[i][4][:lines[i][4].find(" ")]
  lines[i][4] = lines[i][4].replace("n.e", "NA")
  lines[i][4] = lines[i][4].replace("n.d", "NA")
  lines[i][4] = lines[i][4].replace(".", "")
  lines[i][4] = lines[i][4].replace(" ", "")

  lines[i][3] = re.sub("\s+", " ", lines[i][3])
  lines[i][3] = re.sub("^\s+", "", lines[i][3])
  lines[i][3] = lines[i][3].replace("'", "")
  lines[i][3] = lines[i][3].replace("\\r", " ")
  lines[i][3] = str.lower(lines[i][3])
  if "cie" in lines[i][3]:
    cie = lines[i][3][lines[i][3].find("cie-10a rev.") + 13:]
    lines[i][3] = lines[i][3][:lines[i][3].find("cie-10a rev.") - 1]
    lines[i].append(cie)
```

Simplificación y resultado

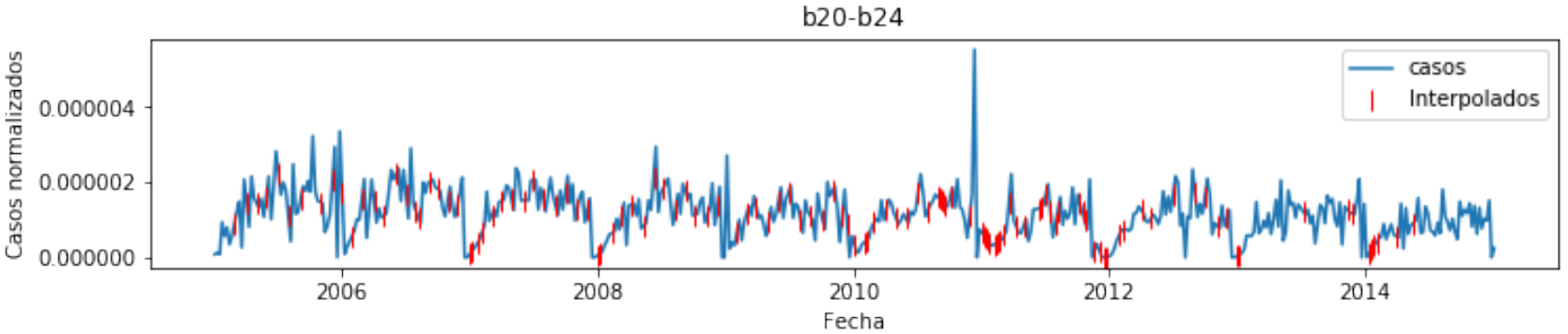
awk

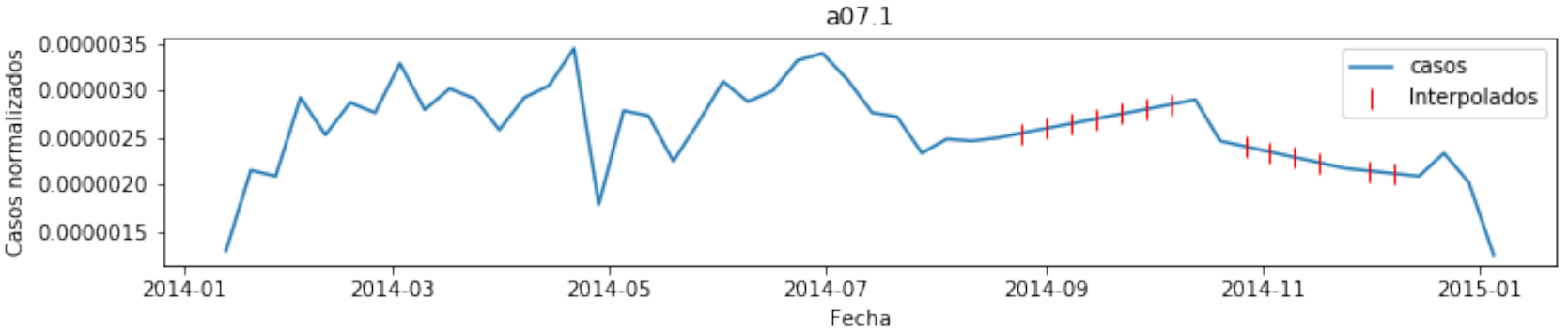
```
awk -F ',' '{print $4, $6 }' sort | uniq -c
```

Resultados nacionales (23 617 registros)

Año	SE	Enfermedad	Casos	CIE
2013	37	Cólera	0	A01
2006	52	Mordeduras por otros mamíferos	117	W55
2014	20	Paludismo por P. Vivax	8	B51

Formato(19 434 registros)



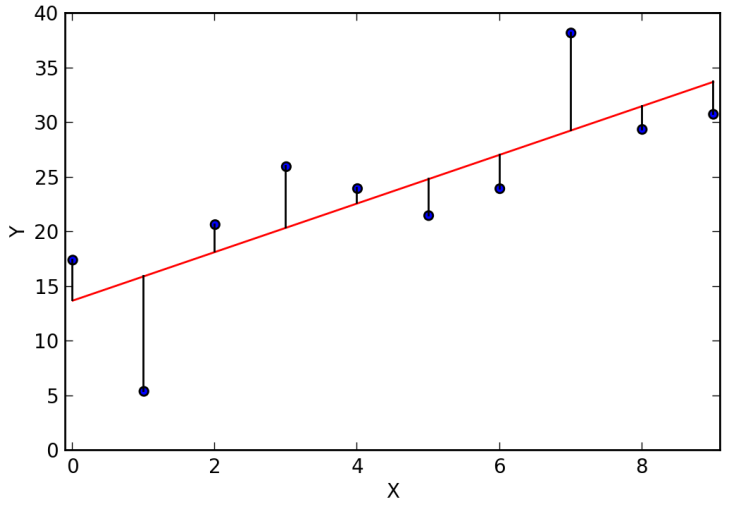


Software para series de tiempo

- `Python v3` [32]: Lenguaje de programación de alto nivel.
- `Pandas` [26]: *Python Data Analysis Library*.
- `datetime` [33]: Manipulación de fechas y horarios.
- `interpolate` [25]: Interpolación por frecuencia semanal.
- `detrend` [39]: Eliminación de la tendencia.

Regresión lineal

Recurso: `linregress` de la librería `SciPy` [40]
$\mathcal{O}(p^2 n + p^3)$ [38]



$$\hat{y}(t, \omega) = \omega_0 + \omega_1 x_1 + \ldots + \omega_t x_t. \tag{1}$$

$$\text{mín} \left(\sum_t (y_t - \hat{y}_t)^2 \right). \tag{2}$$

Tendencia

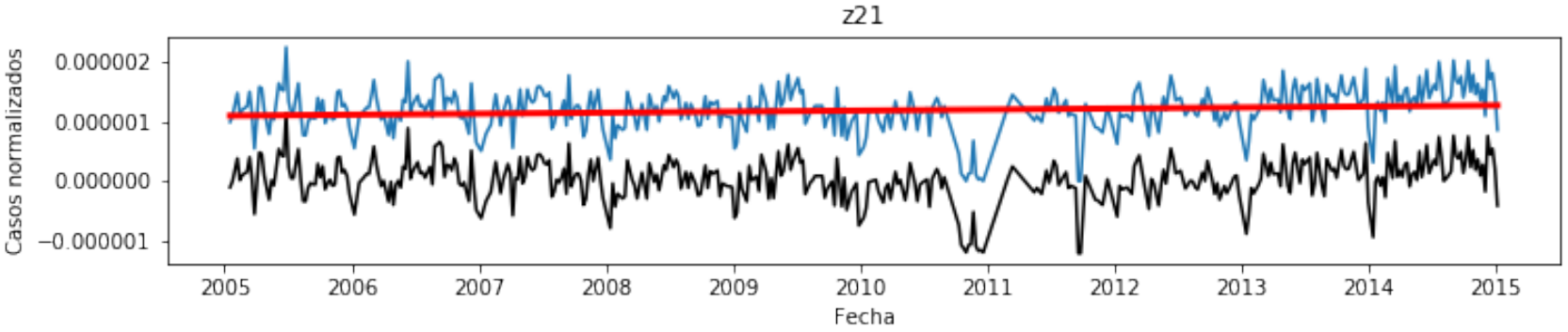


Figura: Infección asintomática por VIH.

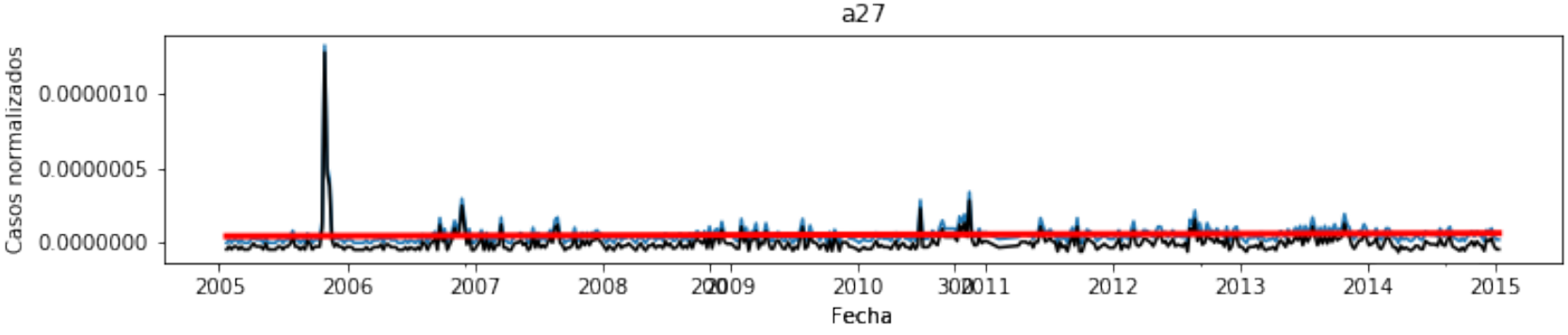


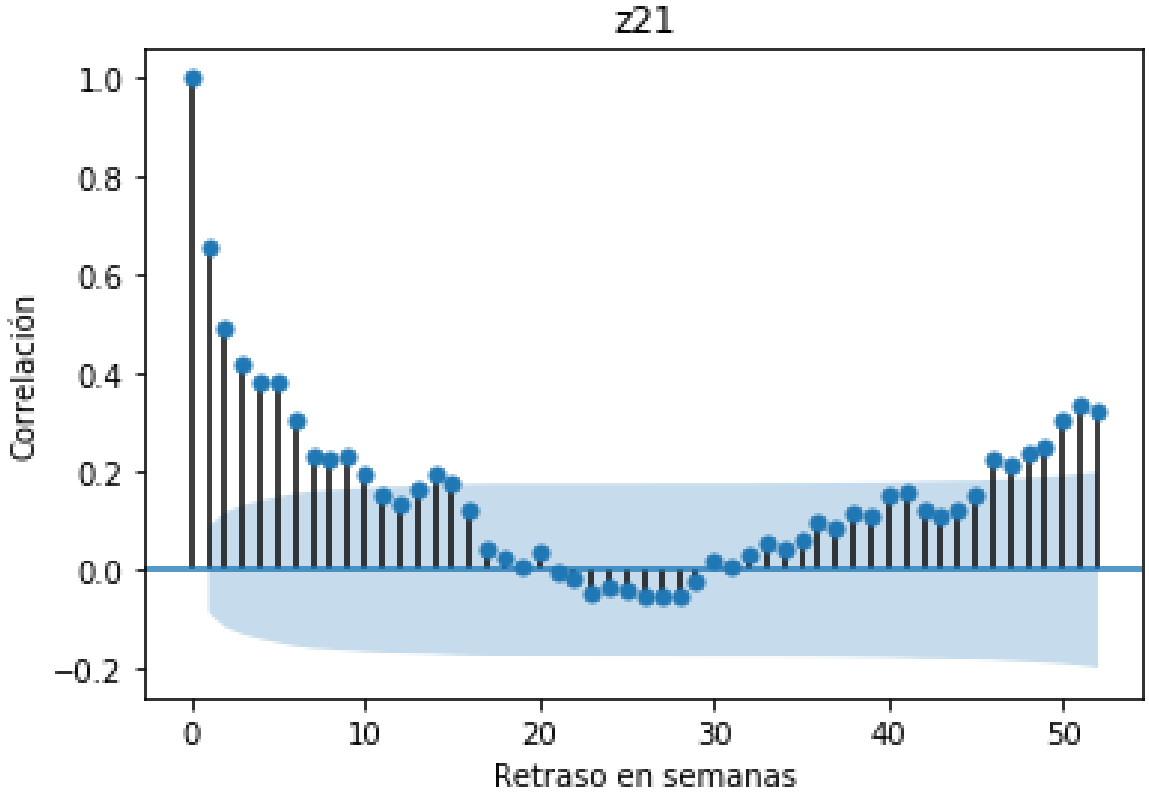
Figura: Tos ferina.

Autocorrelaciones

Recurso: `acf` de la librería `StatsModels` [30]

$$\gamma_x(h) = \text{CoV}(X_{t+h}, X_t) \tag{3}$$

$$\hat{p}_x(h) = \frac{\gamma_x(h)}{\gamma_x(0)} = \text{Cor}(X_{t+h}, X_t). \tag{4}$$



Selección de características

Recurso: *Umbral de varianza* de `scikit-learn` [10];

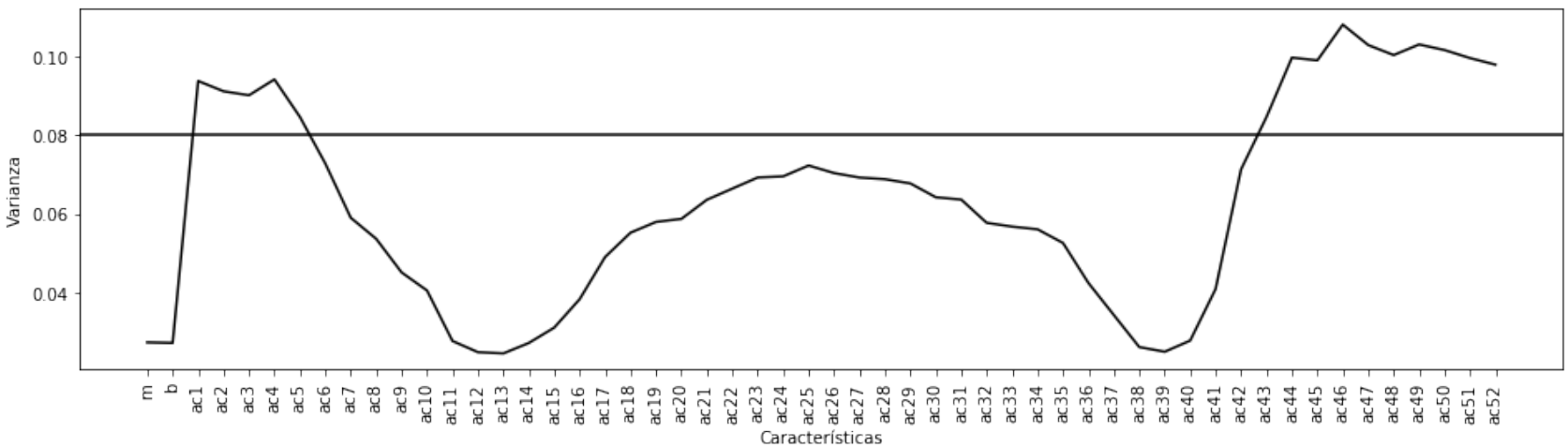


Figura: Características con varianza superior a 0.08

k-medias

Recurso: k-means de scikit-learn [9]

- $X = \{x_i\}, i = 1, \ldots, n$ puntos d-dimensionales
- $C = \{c_j, j = 1, \ldots, k\}$ centros
- μ_j: media de los puntos $x_i \in c_j$

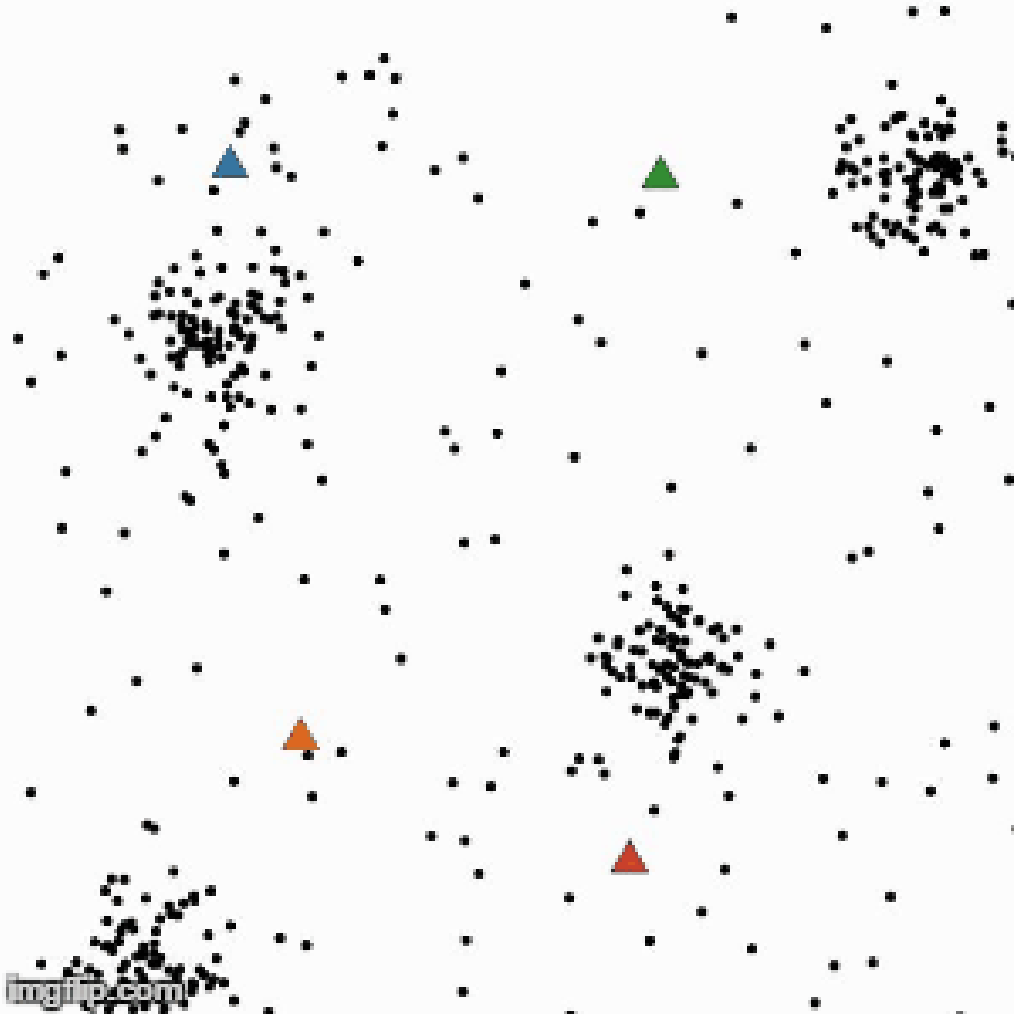
$$J(C) = \sum_{k=1}^{K} \sum_{x_i \in c_k} \|x_i - \mu_k\|^2 \tag{5}$$

$$\text{mín}(J(C)) \tag{6}$$

NP-duro [24]

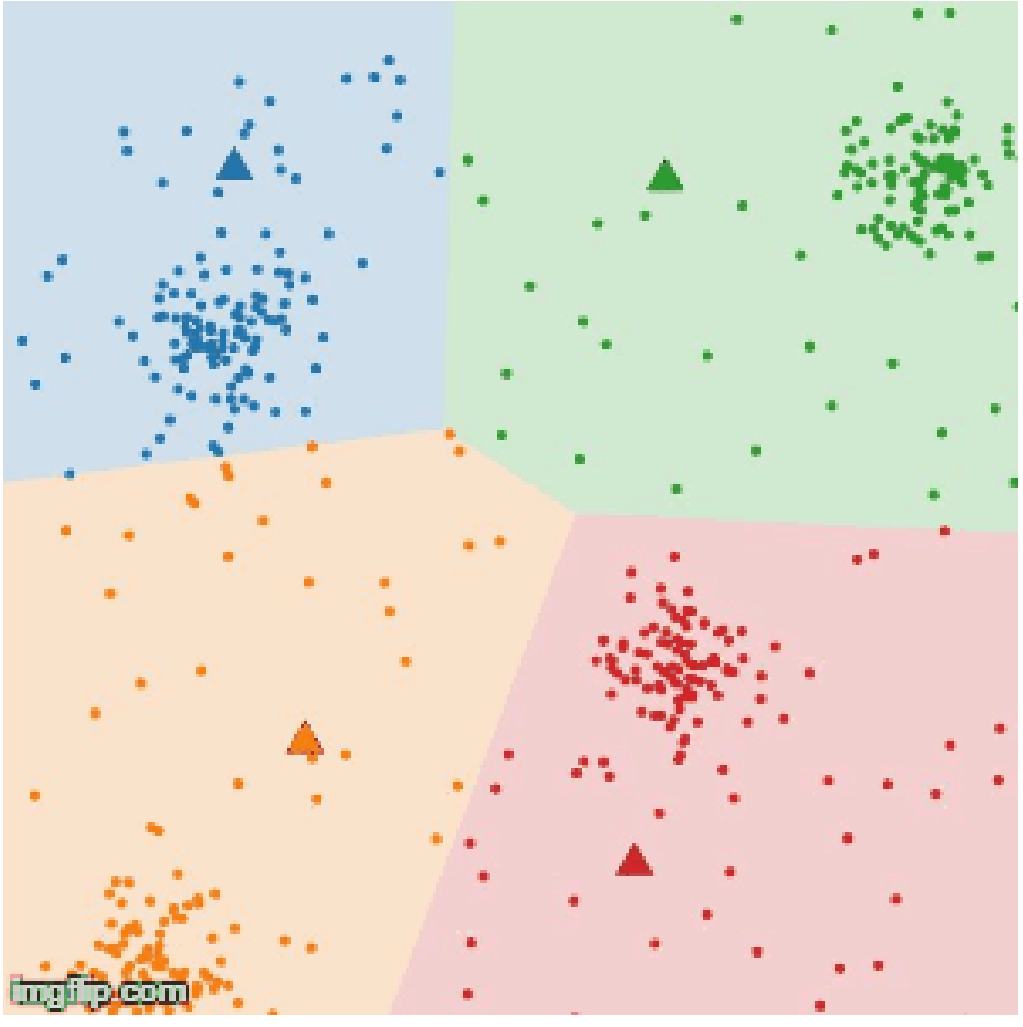
Algoritmo

1. Seleccionar un número k de grupos.
2. Asignarles una posición C_j inicial aleatoria.



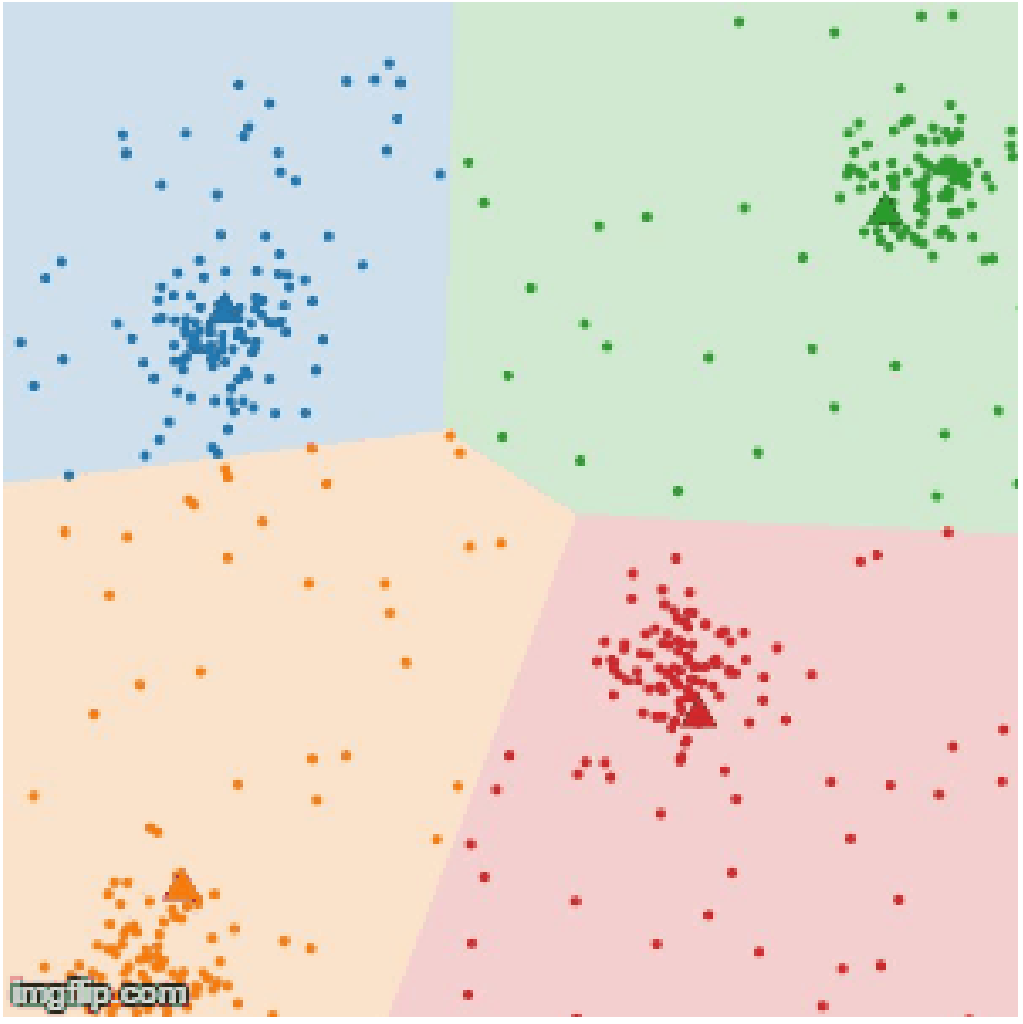
Algoritmo

3. Asociar cada punto con el centro C_j más cercano.



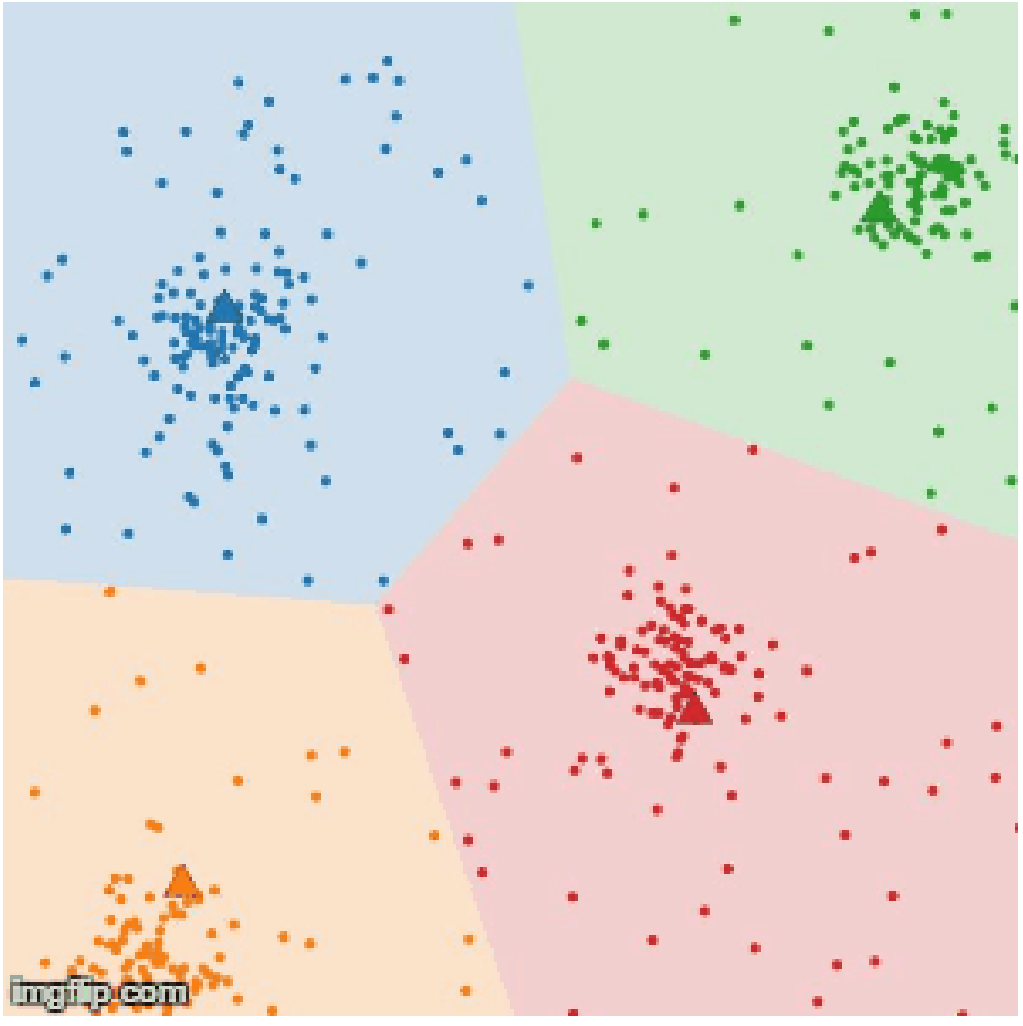
Algoritmo

4. Encontrar la media de cada grupo μ_j.
5. Mover cada centro C_j a dicha media μ_j.



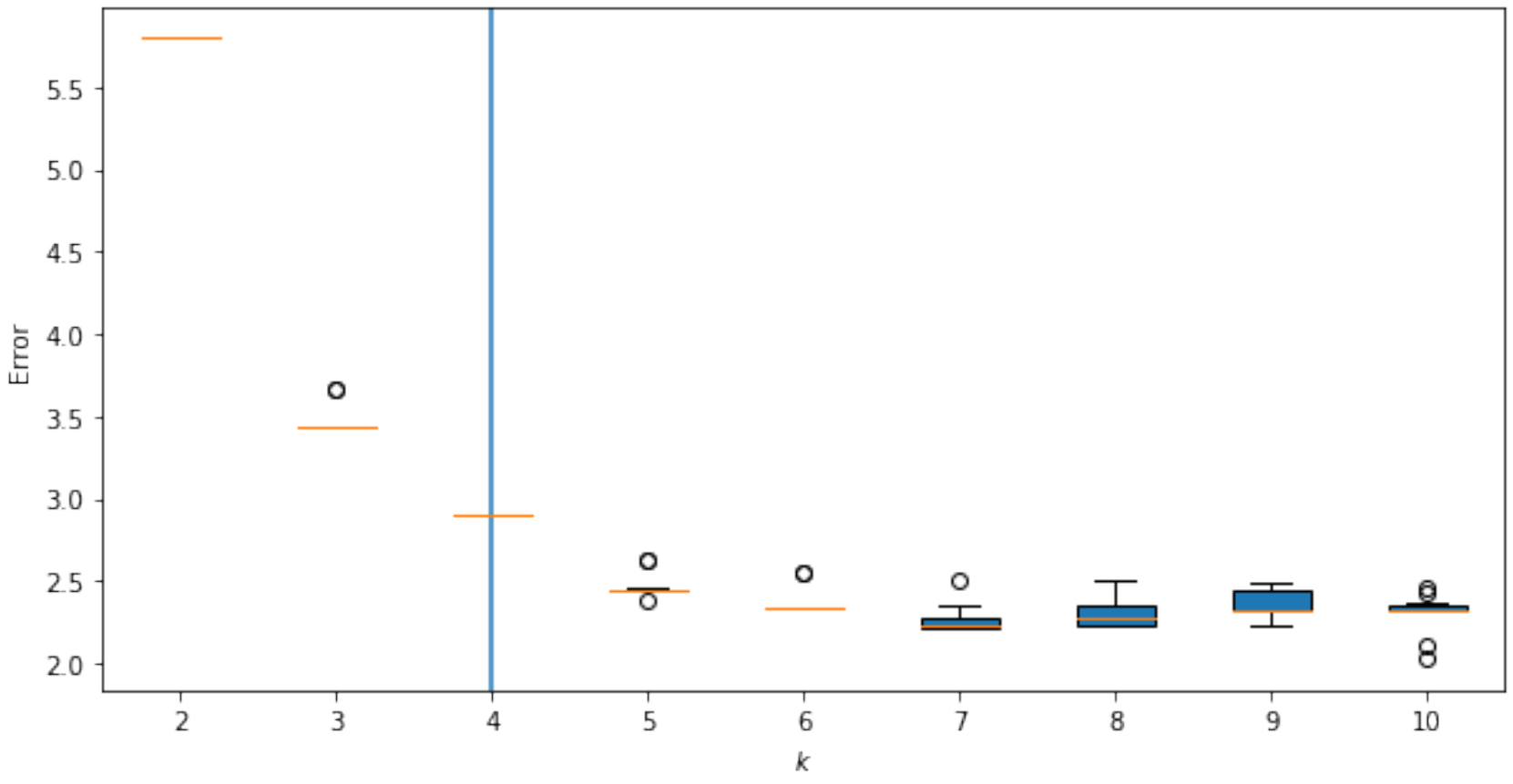
Algoritmo

6. Medir $J(C)$ y si es menor que el anterior, repetir desde el paso 4 [5, 18].



Método del codo [36]

Recurso: `kneedle` [37]



- Comparación con otros algoritmos de agrupamiento.
- Usar otras características y medidas de distancias.
- Comparar con registros diarios de consultas.
- Usar grupos resultantes para mejorar algoritmos de clasificación.

Gracias por su atención.

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