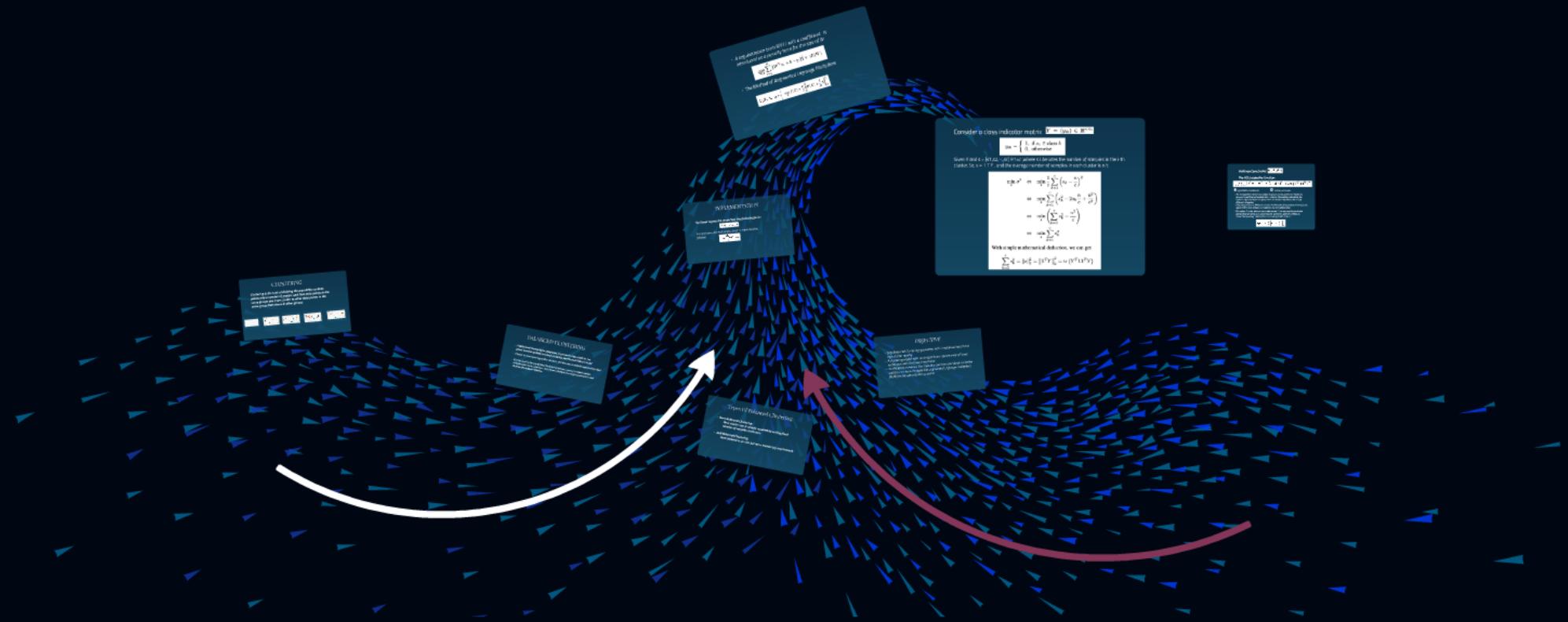


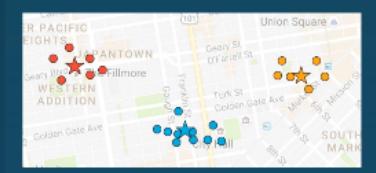
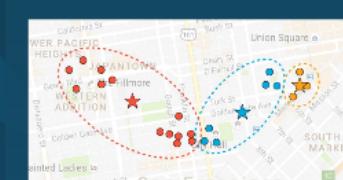
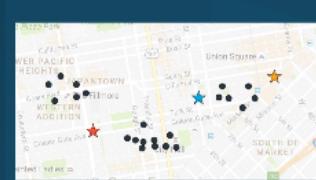
# Balanced Clustering with Least Square Regression

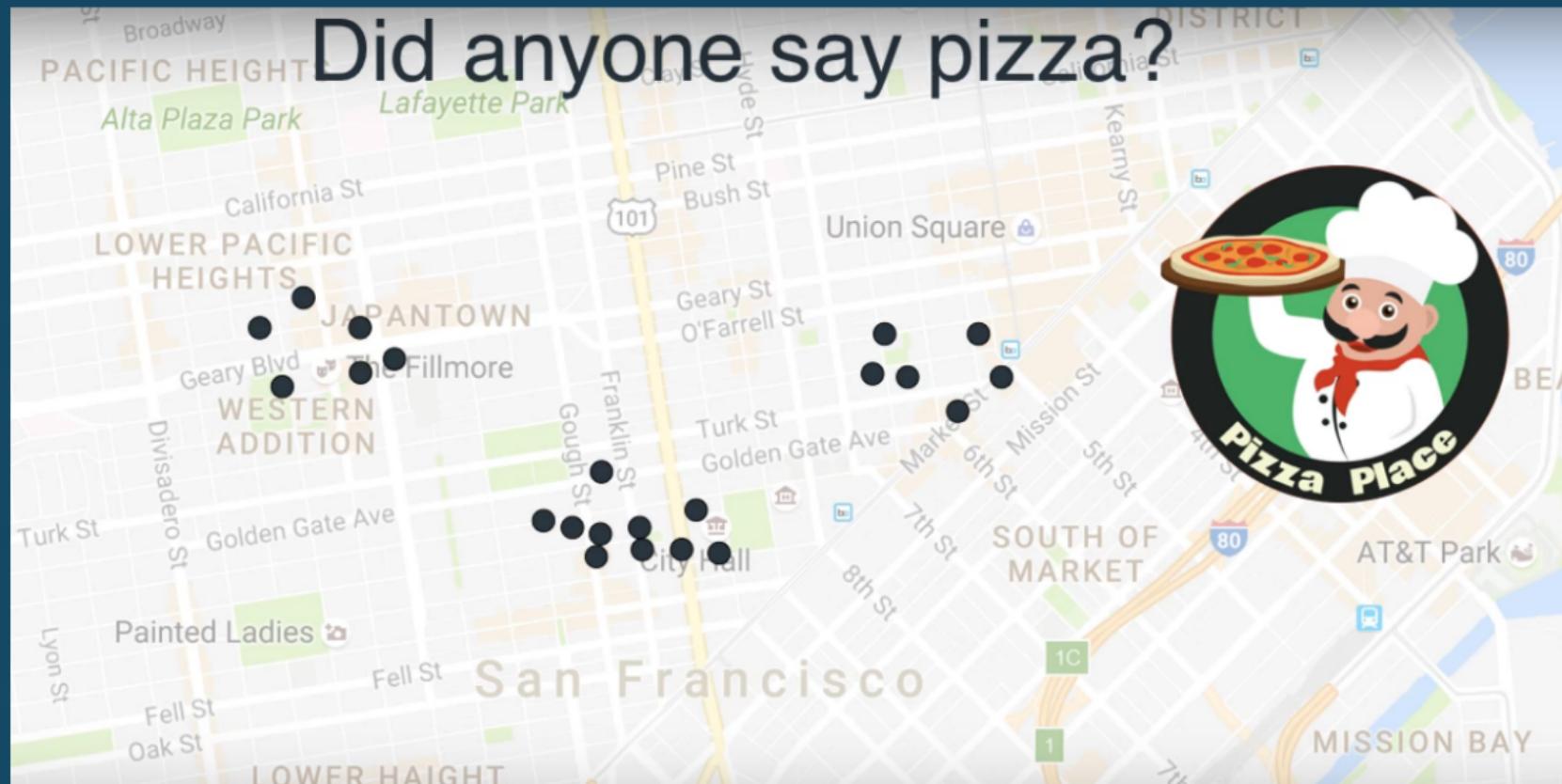


# Balanced Clustering with Least Square Regression

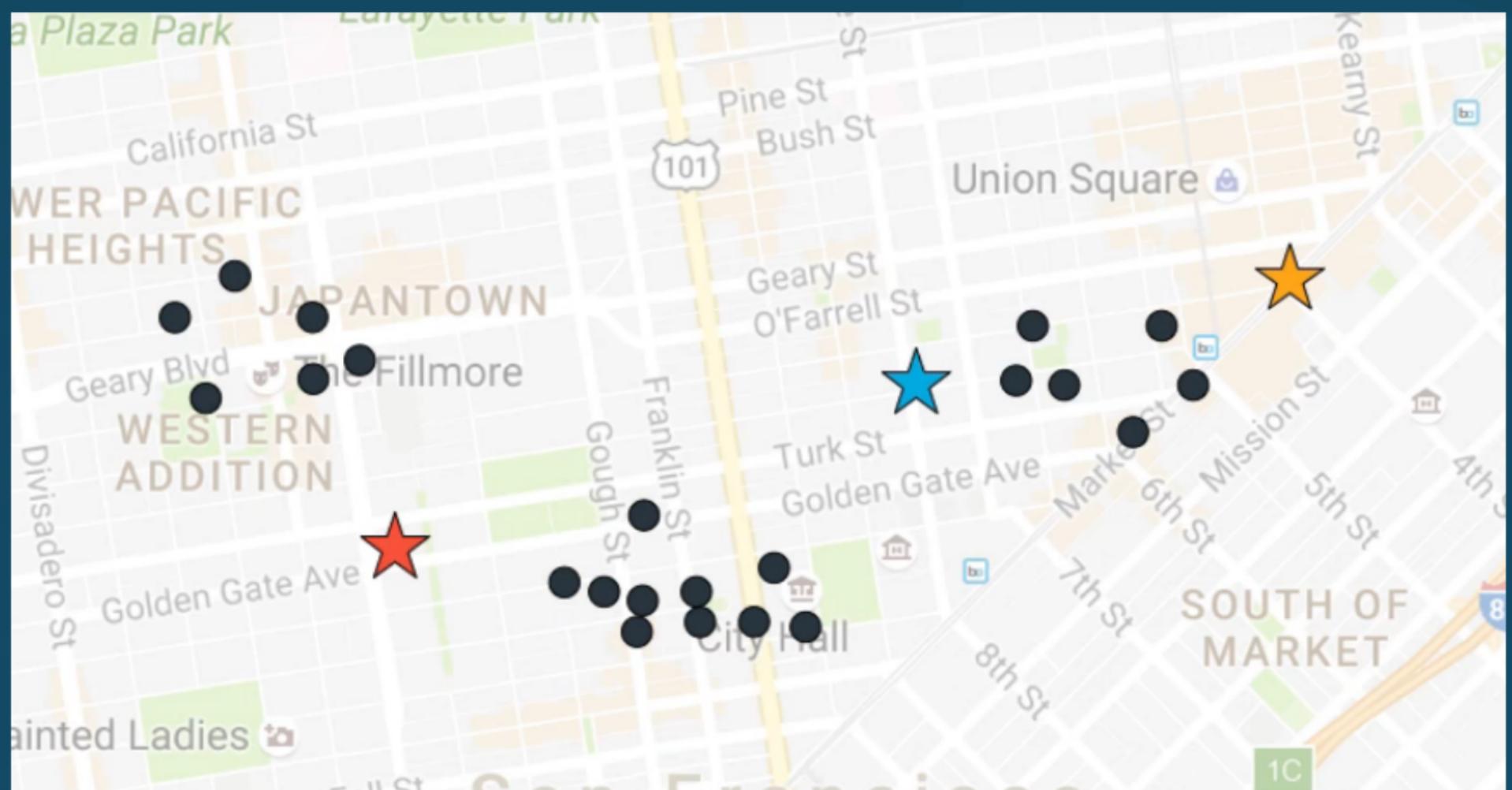
# CLUSTERING

***Clustering is the task of dividing the population or data points into a number of groups such that data points in the same groups are more similar to other data points in the same group than those in other groups***

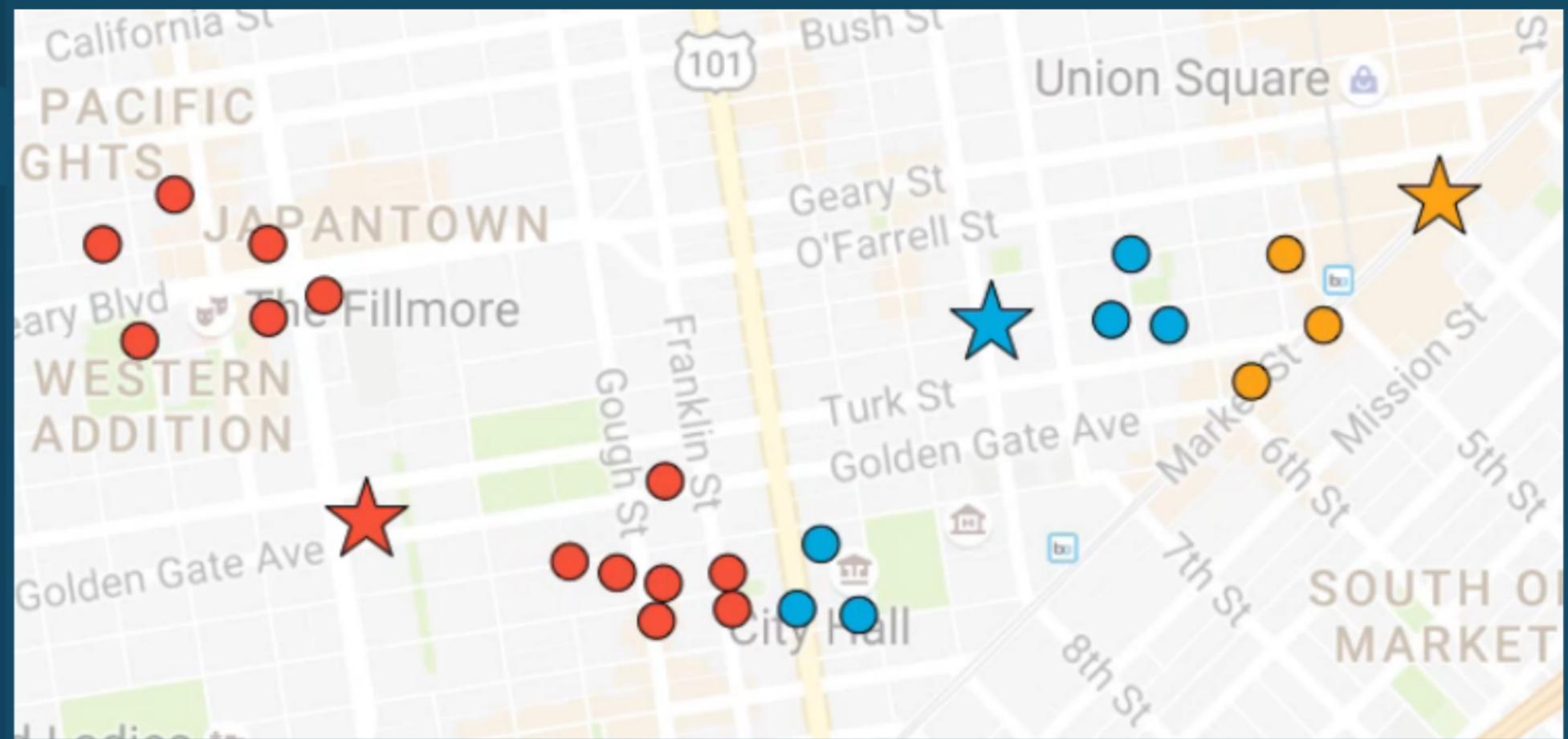




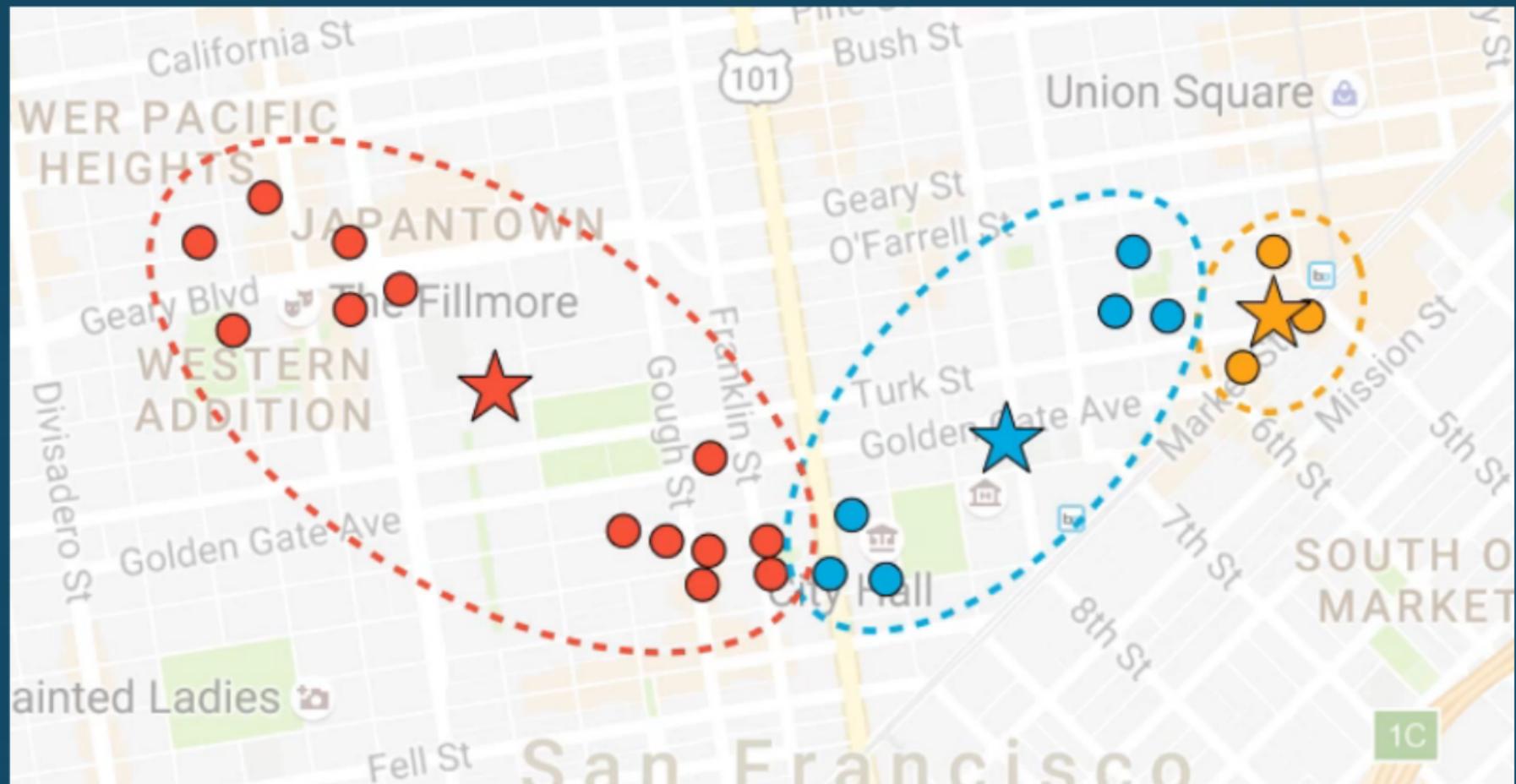
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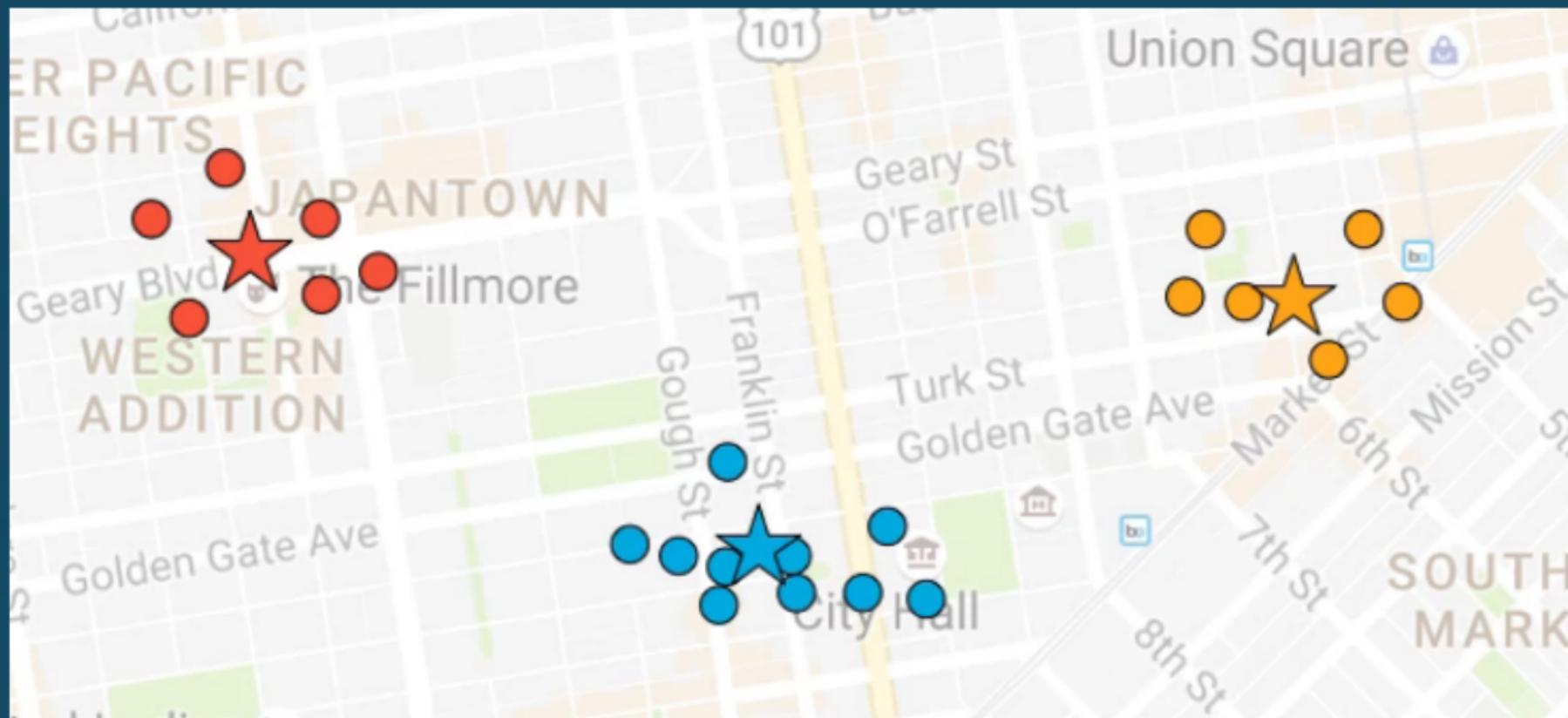
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# BALANCED CLUSTERING

- *A Balanced Clustering is supposed to prevent a too small or too great number of data points from being partitioned into a cluster*
- *It tends to avoid forming outlier clusters, and thus has beneficial regularizing effect*
- *Can be used in the energy load balance of wireless sensor networks where unbalanced cluster structure may cause unbalanced energy consumption and shorten the network lifetime*

# Types Of Balanced Clustering

- ***Hard-Balanced Clustering:***  
*Here cluster size is strictly required by setting fixed number of samples in clusters*
- ***Soft-Balanced Clustering:***  
*Here balance is an aim but not a mandatory requirement.*

# OBJECTIVE

- *Soft Balanced Clustering-guarantee both a balanced result and high cluster quality*
- *A clustering model with minimized least square error of linear regression with Balanced constraint*
- *To efficiently minimize the objective function and obtain a better solution, we have to apply the augmented Lagrange multipliers (ALM) for the optimization problem*

# IMPLEMENTATION

*The linear regression model has the following form:*

$$f(x) = x^T w + b$$

*In regression, the estimation error is minimized as follows:*

$$\min \sum_{i=1}^n e(f(x_i), y_i)$$

- A regularization term  $R(W)$  with a coefficient  $\gamma$  is introduced as a penalty term for the size of  $W$

$$\min_{W,b} \sum_{i=1}^n \|W^T x_i + b - y_i\|_2^2 + \gamma R(W)$$

- The Method of Augmented Lagrange Multipliers

$$L(X, \Lambda, \mu) = \min_X f(X) + \frac{\mu}{2} \left\| H(X) + \frac{1}{\mu} \Lambda \right\|_F^2$$

Consider a class indicator matrix  $Y = (y_{ik}) \in \mathbb{R}^{n \times c}$

$$y_{ik} = \begin{cases} 1, & \text{if } x_i \in \text{class } k \\ 0, & \text{otherwise} \end{cases}$$

Given  $Y$  and  $s = [s_1, s_2, \dots, s_c]^T \in \mathbb{R}^{1 \times c}$ , where  $s_i$  denotes the number of samples in the  $i$ -th cluster. So,  $s = 1^T Y$ , and the average number of samples in each cluster is  $n/c$

$$\begin{aligned} \min_s \sigma^2 &\Leftrightarrow \min_s \frac{1}{c} \sum_{k=1}^c \left( s_k - \frac{n}{c} \right)^2 \\ &\Leftrightarrow \min_s \sum_{k=1}^c \left( s_k^2 - 2s_k \frac{n}{c} + \frac{n^2}{c^2} \right) \\ &\Leftrightarrow \min_s \left( \sum_{k=1}^c s_k^2 - \frac{n^2}{c} \right) \\ &\Leftrightarrow \min_s \sum_{k=1}^c s_k^2 \end{aligned}$$

With simple mathematical deduction, we can get

$$\sum_{k=1}^c s_k^2 = \|s\|_2^2 = \|1^T Y\|_2^2 = \text{tr}(Y^T 1 1^T Y)$$

**Balance Constraint:**  $\text{tr}(Y^T \mathbf{1} \mathbf{1}^T Y)$

**The BCLS objective function:**

$$\min_{W, b, Y \in \text{Ind}} \|X^T W + \mathbf{1} b^T - Y\|_F^2 + \gamma \|W\|_F^2 + \lambda \text{tr}(Y^T \mathbf{1} \mathbf{1}^T Y)$$

$\gamma$ -regularization parameter

$\lambda$  -balance parameter

- *The minimization of the least square regression term guides the clustering process to partition data points into c clusters. Meanwhile, minimizing the balance regularization term guarantees the balanced partitioning among different categories.*
- *Since the problem is NP-hard, it is very hard to solve it in polynomial time. So, we apply ALM to help obtain good solutions for the optimization*
- *We replace Y in the balance term with matrix Z into an equality constraint optimization problem and approximately obtain the optimal solution by alternatively solving Y with Z fixed and solving Z with Y fixed.*

$$\min_X f(X) + \frac{\mu}{2} \left\| H(X) + \frac{1}{\mu} \Lambda \right\|_F^2$$

## We get the final optimization problem for our BCLS method

$$\min_{W, b, Y \in Ind, Z} \|X^T W + \mathbf{1}b^T - Y\|_F^2 + \gamma \|W\|_F^2 + \lambda \text{tr}(Z^T \mathbf{1}\mathbf{1}^T Z) + \frac{\mu}{2} \left\| Y - Z + \frac{1}{\mu} \Lambda \right\|_F^2$$

$\mu$

- positive scalar and its value increases slightly after each iteration

$\Lambda$

- estimate of the Lagrange multiplier

- The estimation accuracy improves at every step of iteration.
- It can be solved by alternatively updating the four variables  $W$ ,  $b$ ,  $Y$  and  $Z$

1) With  $Y$  and  $Z$  fixed

$$\min_{W, b} \|X^T W + \mathbf{1}b^T - Y\|_F^2 + \gamma \|W\|_F^2$$

2) simply by setting the derivatives of the objective function with respect to  $W$  and  $b$  to zeros, we have

$$\begin{cases} W = (XX^T + \gamma I_d)^{-1} XY \\ b = \frac{1}{n} Y^T \mathbf{1} \end{cases}$$

3) With  $W$ ,  $b$  and  $Y$

$$\min_Z \lambda \text{tr}(Z^T \mathbf{1}\mathbf{1}^T Z) + \frac{\mu}{2} \left\| Y - Z + \frac{1}{\mu} \Lambda \right\|_F^2$$

**4) Z can be obtained by setting the derivative of the objective function with respect to Z to zero**

$$Z = (\mu I_n + 2\lambda \mathbf{1}\mathbf{1}^T)^{-1} (\mu Y + \Lambda)$$

**5) With W, b and Z fixed, we can transform BCLS eq into:**

$$\min_{Y \in Ind} \|Y - V\|_F^2 + const.$$

*where const. denotes a constant and  $V = (v_{ik}) \ R \ n \times c$ ,  
and*

$$V = \frac{2}{2 + \mu} (X^T W + \mathbf{1} b^T) + \frac{1}{2 + \mu} (\mu Z - \Lambda)$$

**6) Each element of  $Y = (y_{ik}) \ R \ n \times c$  is binary and the sum of each row is 1**

*We can obtain the solution as follows:*

$$y_{ik} = \begin{cases} 1, & \text{if } k = \arg \max_k \{v_{ik}\}_{k=1}^c \\ 0, & \text{otherwise} \end{cases}$$

# Algorithm of the BCLS method

**Input:** Centered dataset  $X = [x_1, x_2, \dots, x_n] \in \mathbb{R}^{d \times n}$ ,  
the number of clusters  $c$ , and parameters  $\gamma$ ,  $\lambda$ , and  $\rho (\rho > 0)$ .

**Output:** Assignment matrix  $Y \in \mathbb{R}^{n \times c}$ .

Initialize  $Y$  randomly, initialize  $\mu$ , and set  $\Lambda = \mathbf{0} \in \mathbb{R}^{n \times c}$ .

**Repeat**

1. Obtain  $W$  and  $b$  by solving the problem in Eq. (14) with the solution in Eq. (15);
2. Obtain  $Z$  by solving Eq. (16) with the solution in Eq. (17);
3. Obtain  $Y$  by Eq. (19) and Eq. (21);
4. **Update**  $\Lambda$ :  $\Lambda^{(t+1)} = \Lambda^{(t)} + \mu^{(t)}(Y - Z)$ ;
5. **Update**  $\mu$ :  $\mu^{(t+1)} = \rho\mu^{(t)}$ .

**Until**  $Y - Z \rightarrow \mathbf{0}$  or  $\Lambda$  remains unchanged

**Return**  $Y$ .

$$\min_{W,b} \|X^T W + \mathbf{1} b^T - Y\|_F^2 + \gamma \|W\|_F^2 \quad (14)$$

$$\begin{cases} W = (XX^T + \gamma I_d)^{-1} XY \\ b = \frac{1}{n} Y^T \mathbf{1} \end{cases} \quad (15)$$

$$\min_Z \lambda \text{tr}(Z^T \mathbf{1} \mathbf{1}^T Z) + \frac{\mu}{2} \left\| Y - Z + \frac{1}{\mu} \Lambda \right\|_F^2 \quad (16)$$

$$Z = (\mu I_n + 2\lambda \mathbf{1} \mathbf{1}^T)^{-1} (\mu Y + \Lambda) \quad (17)$$

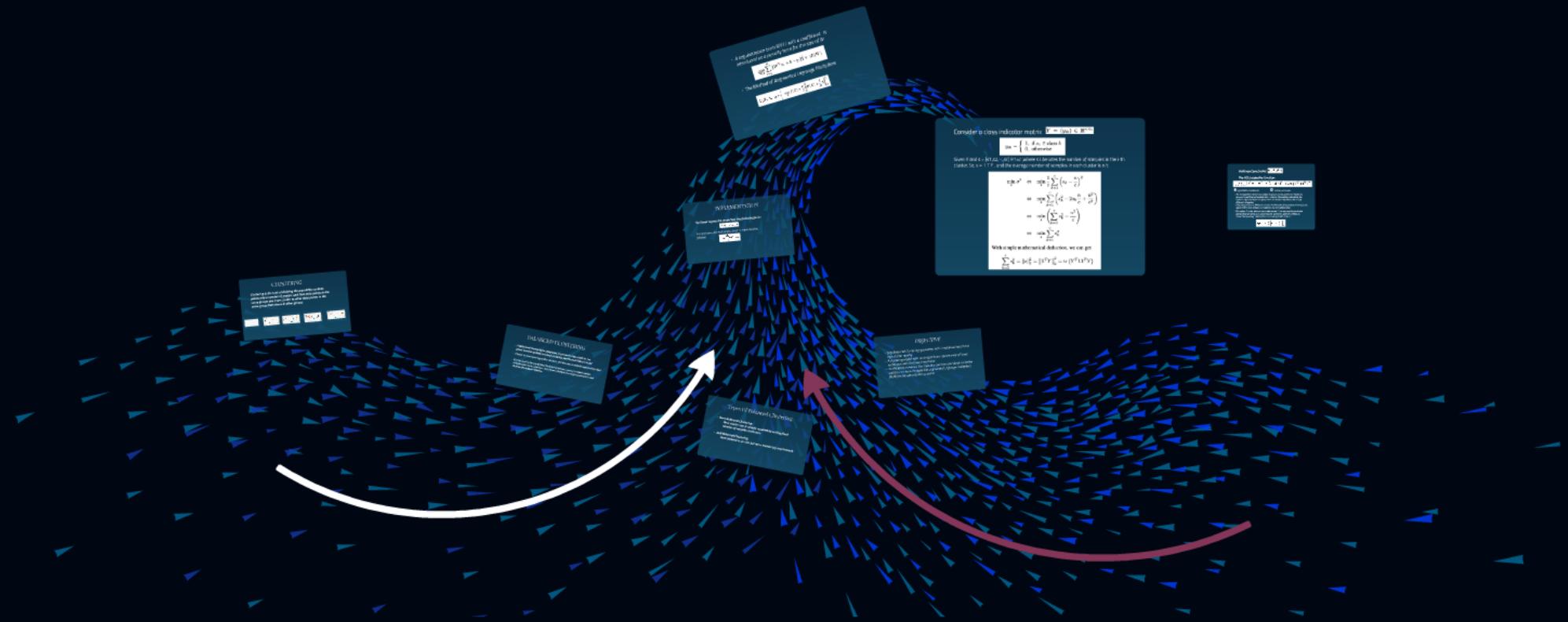
$$V = \frac{2}{2+\mu} (X^T W + \mathbf{1} b^T) + \frac{1}{2+\mu} (\mu Z - \Lambda) \quad (19)$$

$$y_{ik} = \begin{cases} 1, & \text{if } k = \arg \max_k \{v_{ik}\}_{k=1}^c \\ 0, & \text{otherwise} \end{cases} \quad (21)$$

# THANK YOU!!!

<https://github.com/juhi-09/SMAI-BCLS.git>

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# Balanced Clustering with Least Square Regression