

Buyer Targeting Optimization

A Unified Customer Segmentation Perspective

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Background

- Marketing: STP Model
 - **Segmentation:** divide customers into groups of people with common characteristics and needs.
 - **Targeting:** identifies promising customers and allocates marketing resources to increase profits.
 - Positioning
- Usually, accomplished by independent steps.

Background

- For Data Mining...
 - Segmentation → **Clustering**
 - Targeting → **Classification**
- Is it possible to optimize the buyer targeting performance by constructing these tasks in a more integrated way?
- Key idea: use clustering solution to boost the **classification** performance.

Data Sets

Data	Size	Pos_class	Neg_class
Synthetic data	500	200	300
Real – Product A	8,315	1,680	6,635
Real – Product B	22,160	4,232	17,828

- Synthetic data
 - $(x, y, z): (x, y) \in R^2, z \in \{-1, +1\}$
- Real business data
 - 49 integer attributes

Data Sets

Demographics	Values
Company Size	Small Business, Enterprise, Unknown
Industry	Heavy Hitters, Potentials
Job Title	IT Staff, IT Manager, Executive, Researcher, Non-IT, Unknown

Behaviors	Values
Event	Corporate Event, Trade Show, Conference, Webinar, Seminar, Technology Preview
Offer	Official Website, Direct Mail, Email, Call Center, Search Engine, Web Advertising (third party), Social Media
Product	Product Download, Product Free Trial, Product Renewal, Product Activation, Product Training
Activity	Subscribe, Unsubscribe, Active, Inactive

Problem Definition

- Inputs: dataset X with N rows and D discrete attributes, and label attribute y . $(X, y) \subset R^{N \times D} \times \{-1, +1\}$
- Group the customers into K clusters: $\{S_1, S_2 \dots S_K\}$
- learn the classifier C_k for each segment S_k
- Minimize the total loss:

$$J(S, C) = \frac{1}{N} \sum_{i=1}^N \text{loss}(x_i, y_i | C_{l_i}) = \frac{1}{N} \sum_{k=1}^K \sum_{x_i \in S_k} \text{loss}(x_i, y_i | C_k)$$

Problem Definition

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- Loss functions:

- SVM loss: $\text{loss}(x, y | C) = \max\{0, 1 - y \cdot C(x)\}$
- Logit regression: $\text{loss}(x, y | C) = \log(1 + \exp(-y \cdot C(x)))$

Algorithm

- K-classifiers segmentation

Algorithm 1 K-Classifiers Segmentation Algorithm.

Input: $X, Y, K, loss$.

Output: S, C .

```

1: for  $n = 1, \dots, N$  do
2:    $\ell_n \leftarrow \text{rand}\{1, \dots, K\}$ .
3: repeat
4:   #Update step:
5:   for  $k = 1, \dots, K$  do
6:     Learn  $C_k$  based on  $\{x_n, y_n | n \in S_k\}$ .
7:   #Assignment step:
8:   for  $n = 1, \dots, N$  do
9:      $\ell_n \leftarrow \arg \min_k \text{loss}(x_n, y_n | C_k)$ .
10:  until Convergence.

```

Weakness:

Profile Inconsistent

Algorithm

- Profile-consistent algorithm

Algorithm 2 Profile-Consistent Algorithm.

Input: $X, Y, K, M, loss$. X – data, Y – labels, K – clusters, M – sub-regions

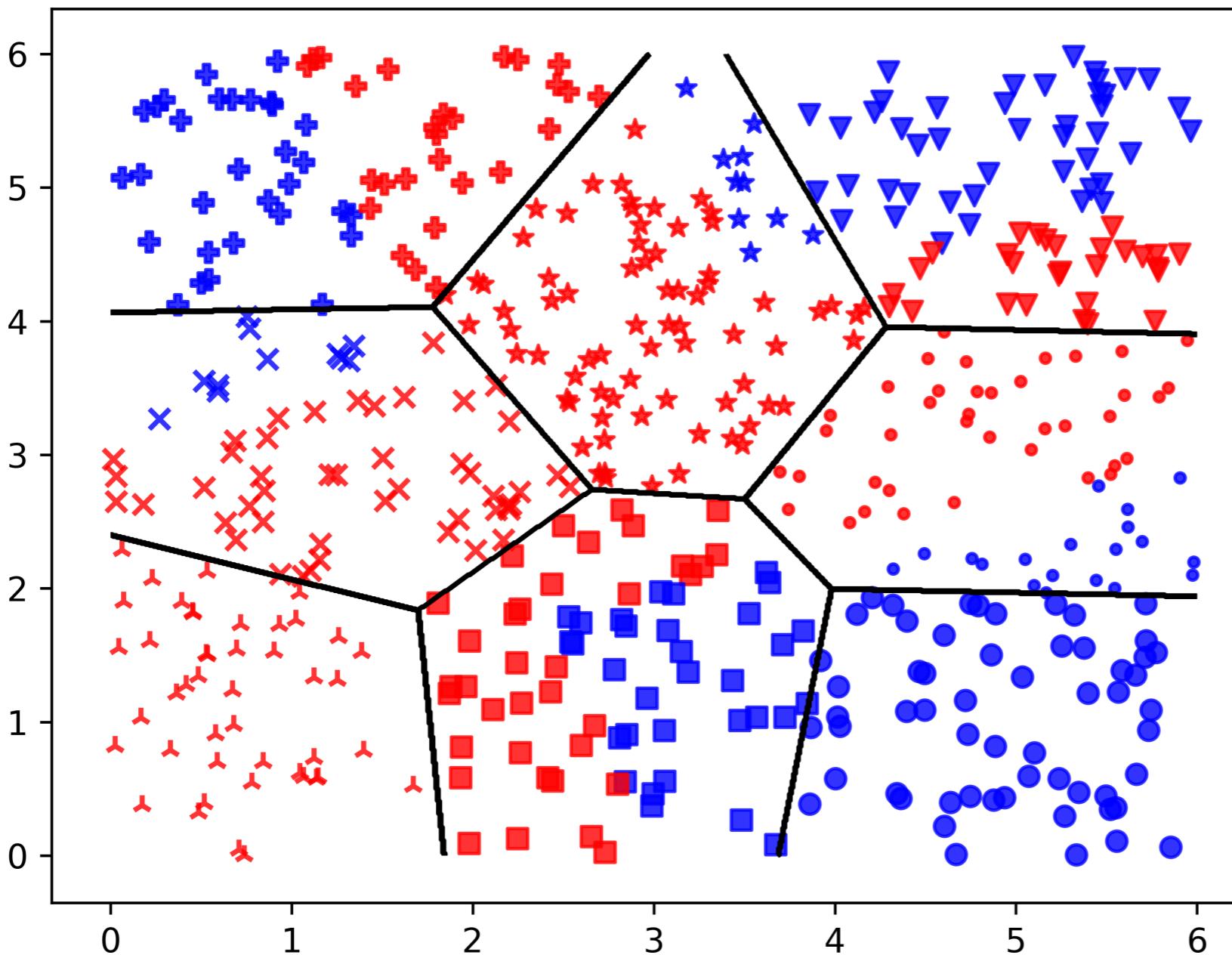
Output: S, C . S – Clusters set, C – Classifiers set

```

1: Randomly select  $M$  seed points to construct the Voronoi
   decomposition  $T_1, \dots, T_M$ .  $T$  –  $M$  sub-regions, generated by K-means
2: for  $m = 1, \dots, M$  do
3:    $\ell_m^t \leftarrow \text{rand}\{1, \dots, K\}$ .  $\mathbf{l}$  – segment assignment; assign randomly.
4: repeat
5:   #Update step:
6:   for  $k = 1, \dots, K$  do      Learn classifiers based on each cluster
7:     Learn  $C_k$  based on  $\{x_n, y_n | n \in S_k\}$ .
8:   #Assignment step:
9:   for  $m = 1, \dots, M$  do      Re-assign sub-regions to cluster based on the loss on
10:     $\ell_m^t \leftarrow \arg \min_k \sum_{n \in T_m} \text{loss}(x_n, y_n | C_k)$ .           corresponding classifiers
11: until Convergence.

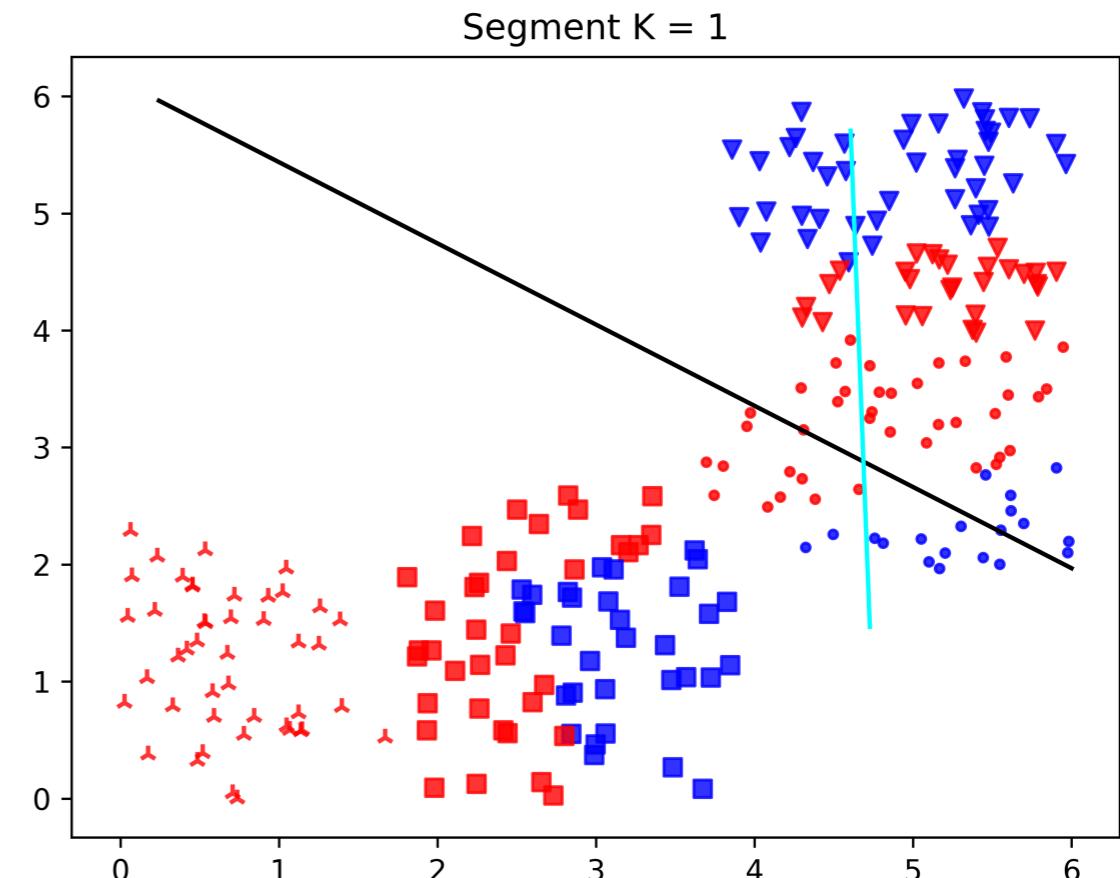
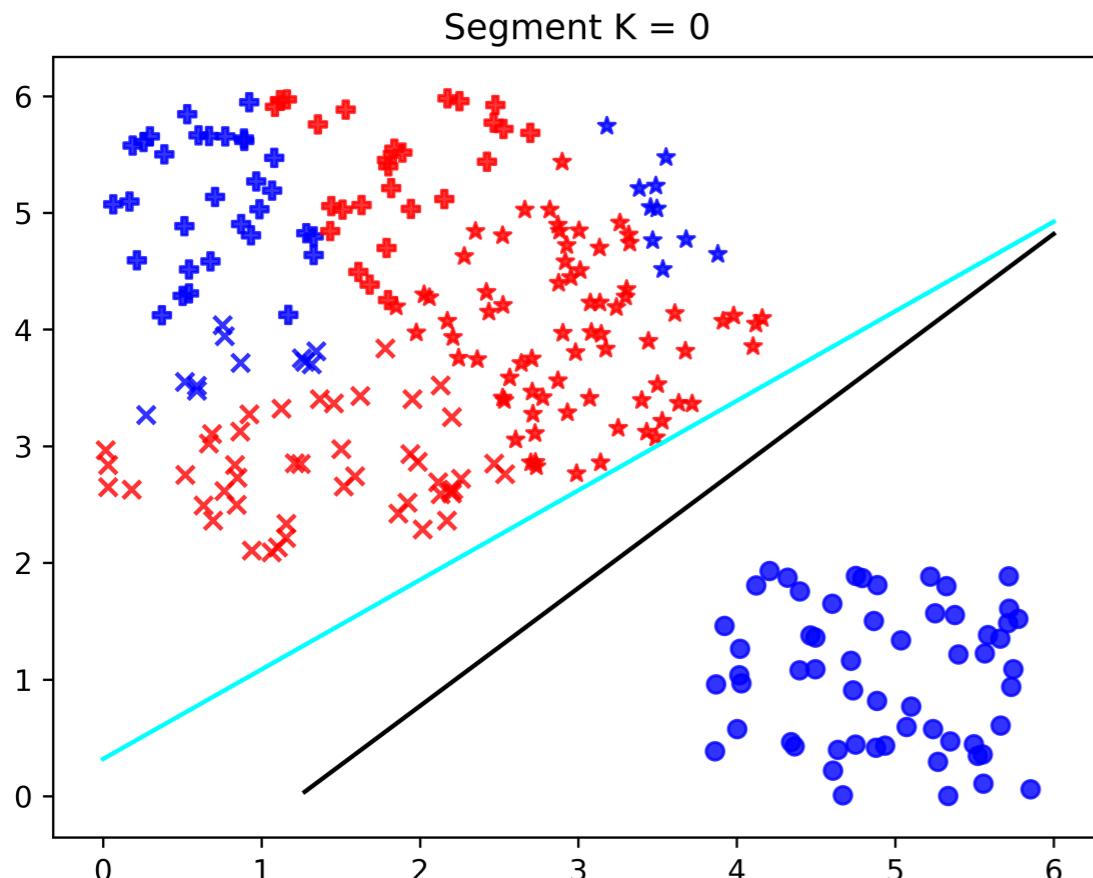
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Sub-region Generate



Blue: $y=1$
Red: $y=-1$
border lines:
separate lines
among subregions

Initial Training

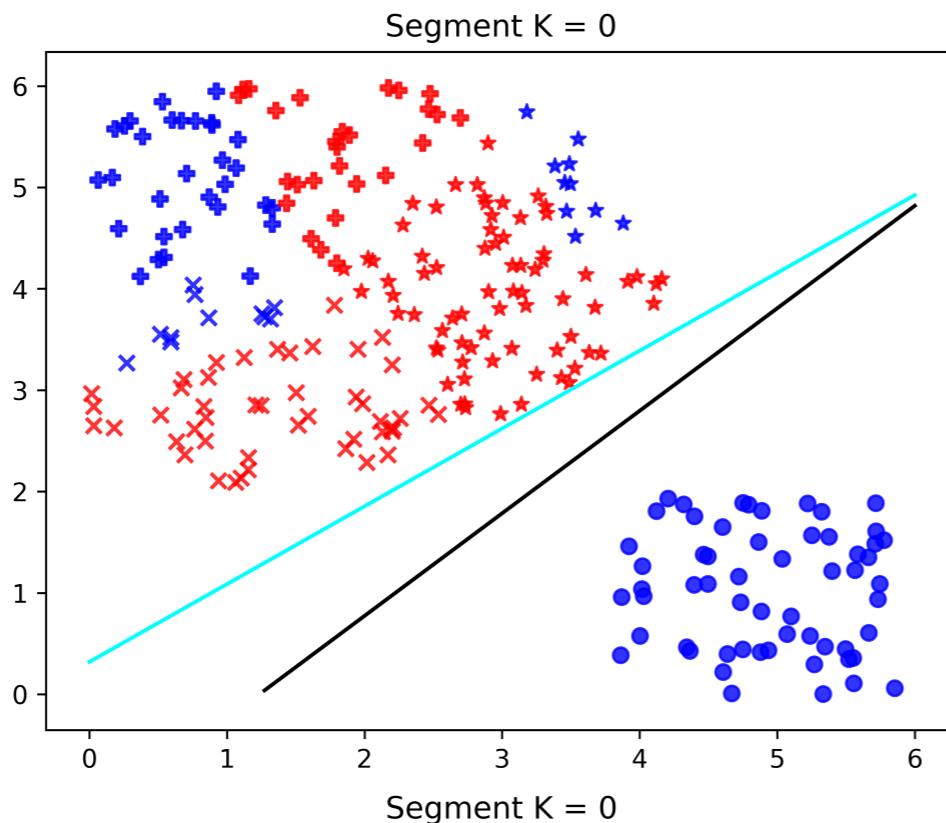


Black line: SVM

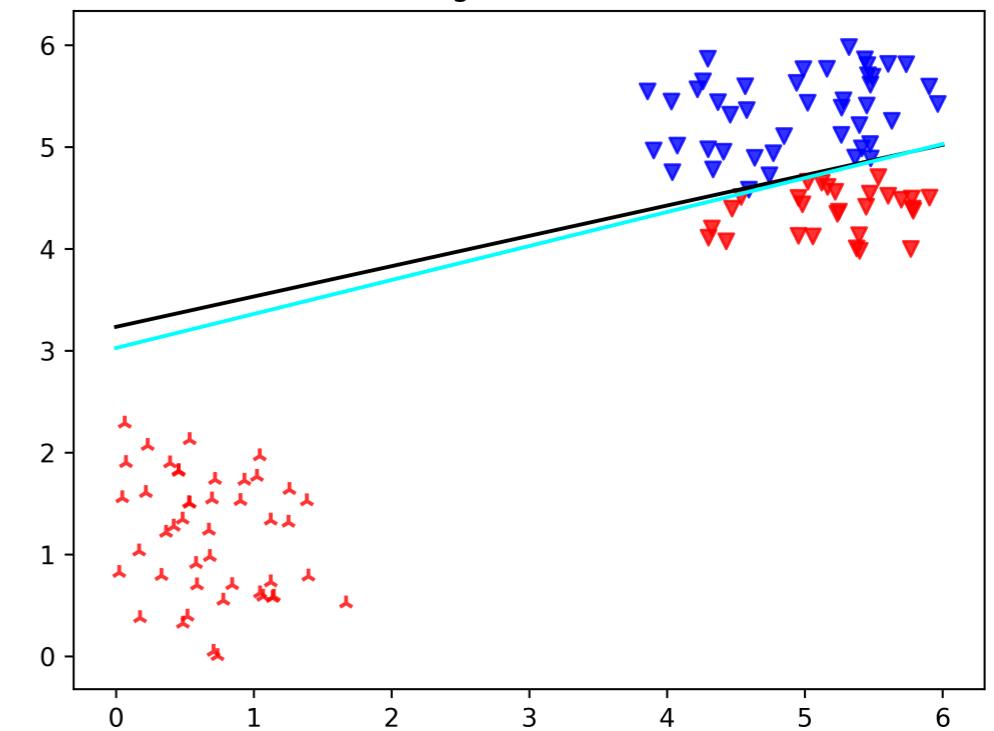
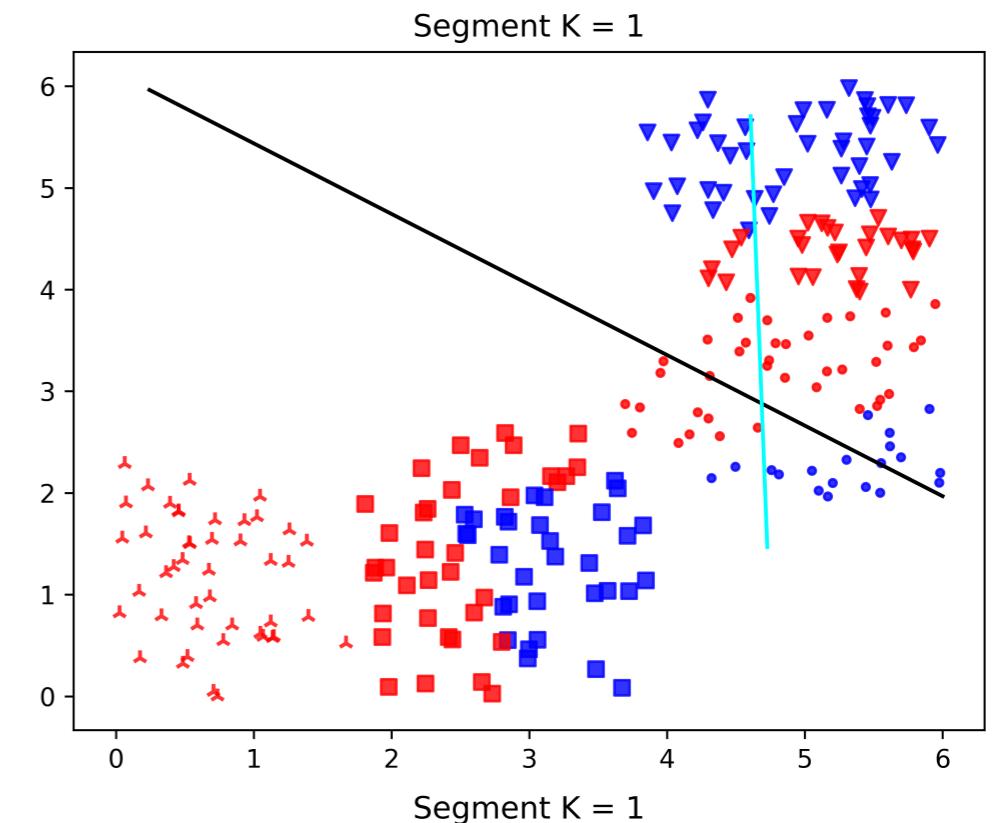
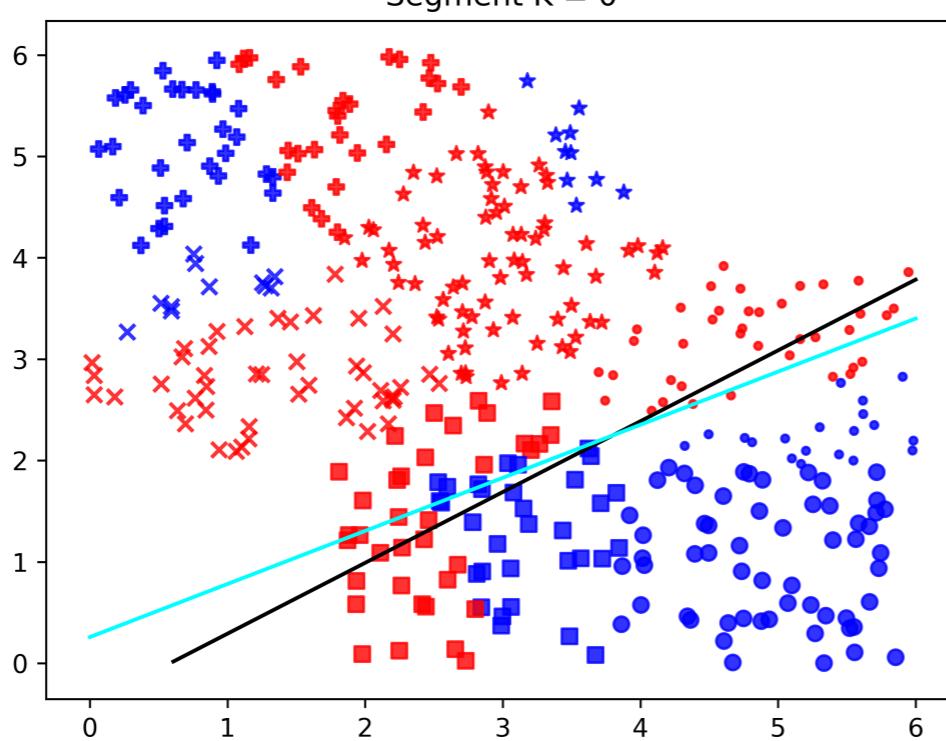
Cyan line: logit regression

First Round Update

Step 0:

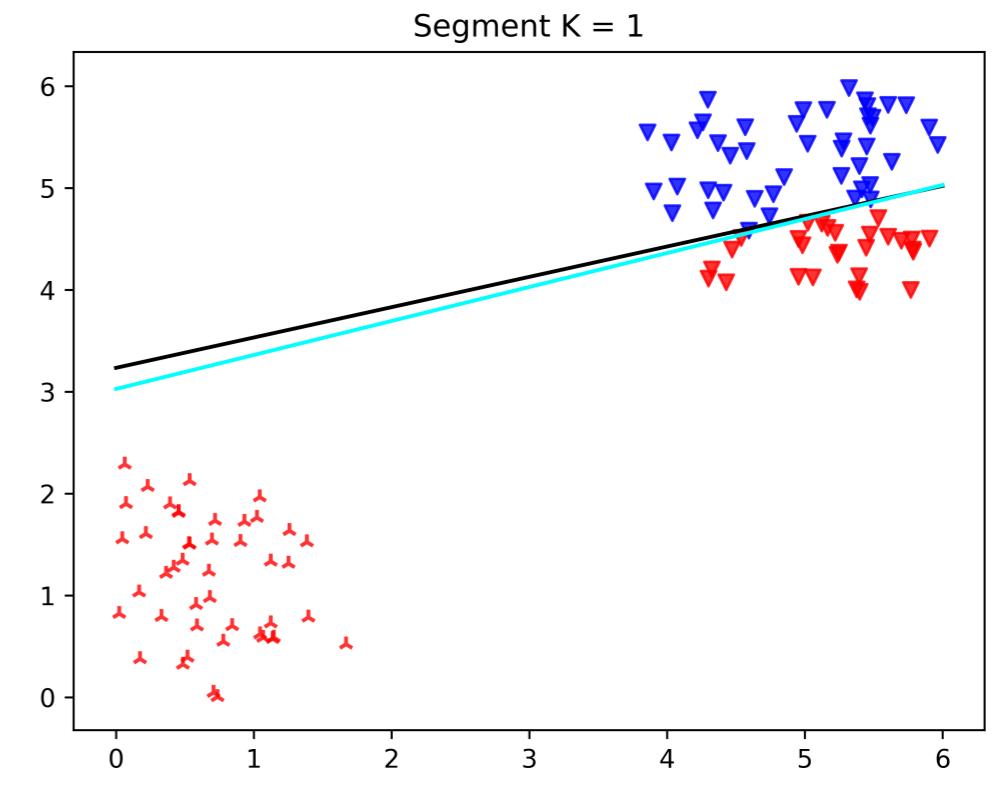
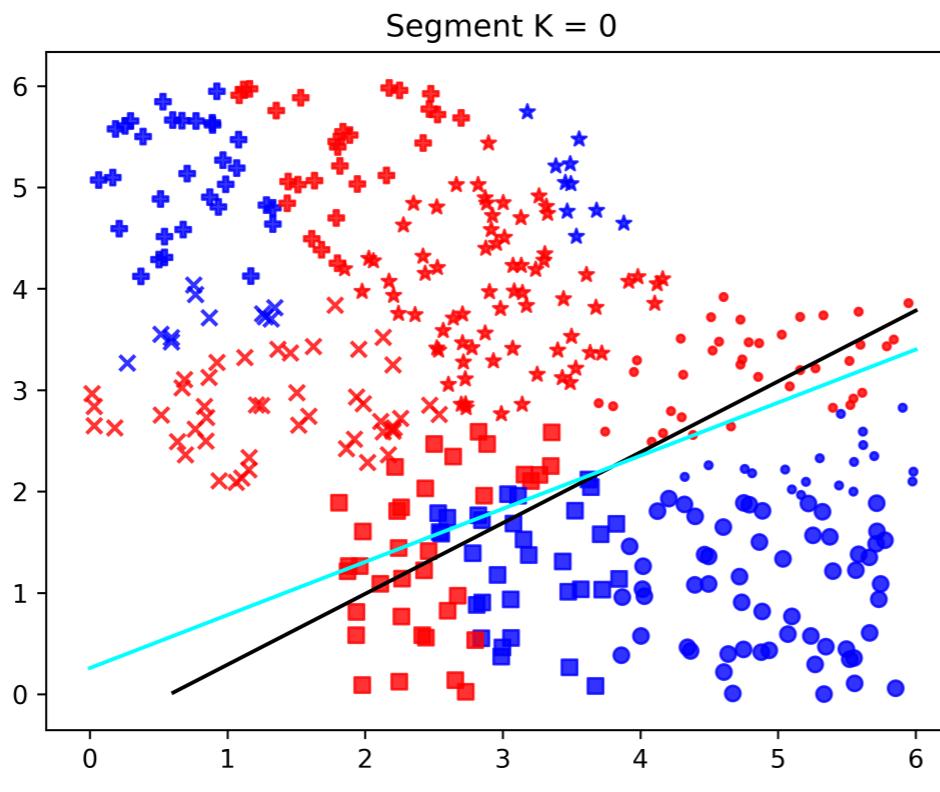


Step 1:

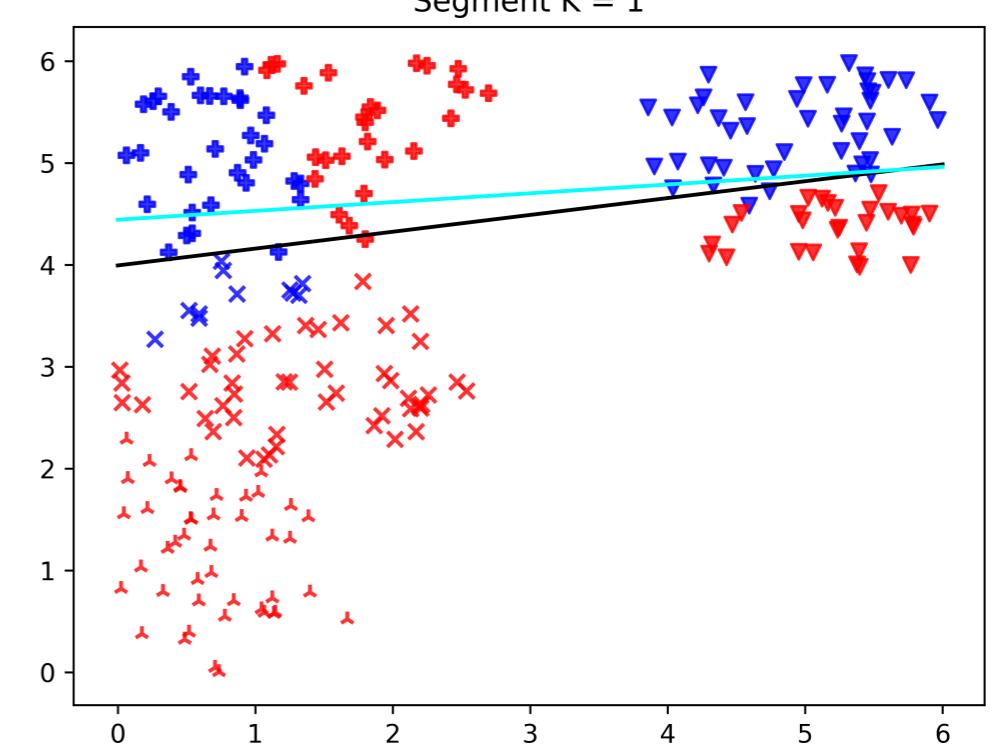
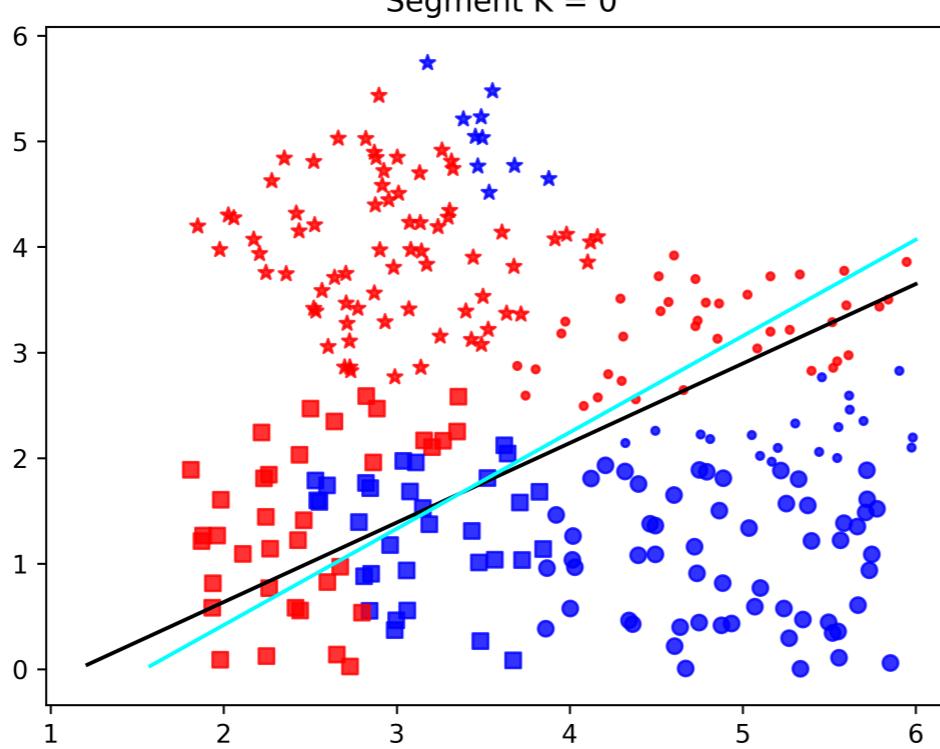


Second Round Update

Step 1:



↓
 Step 2:
 (converge)

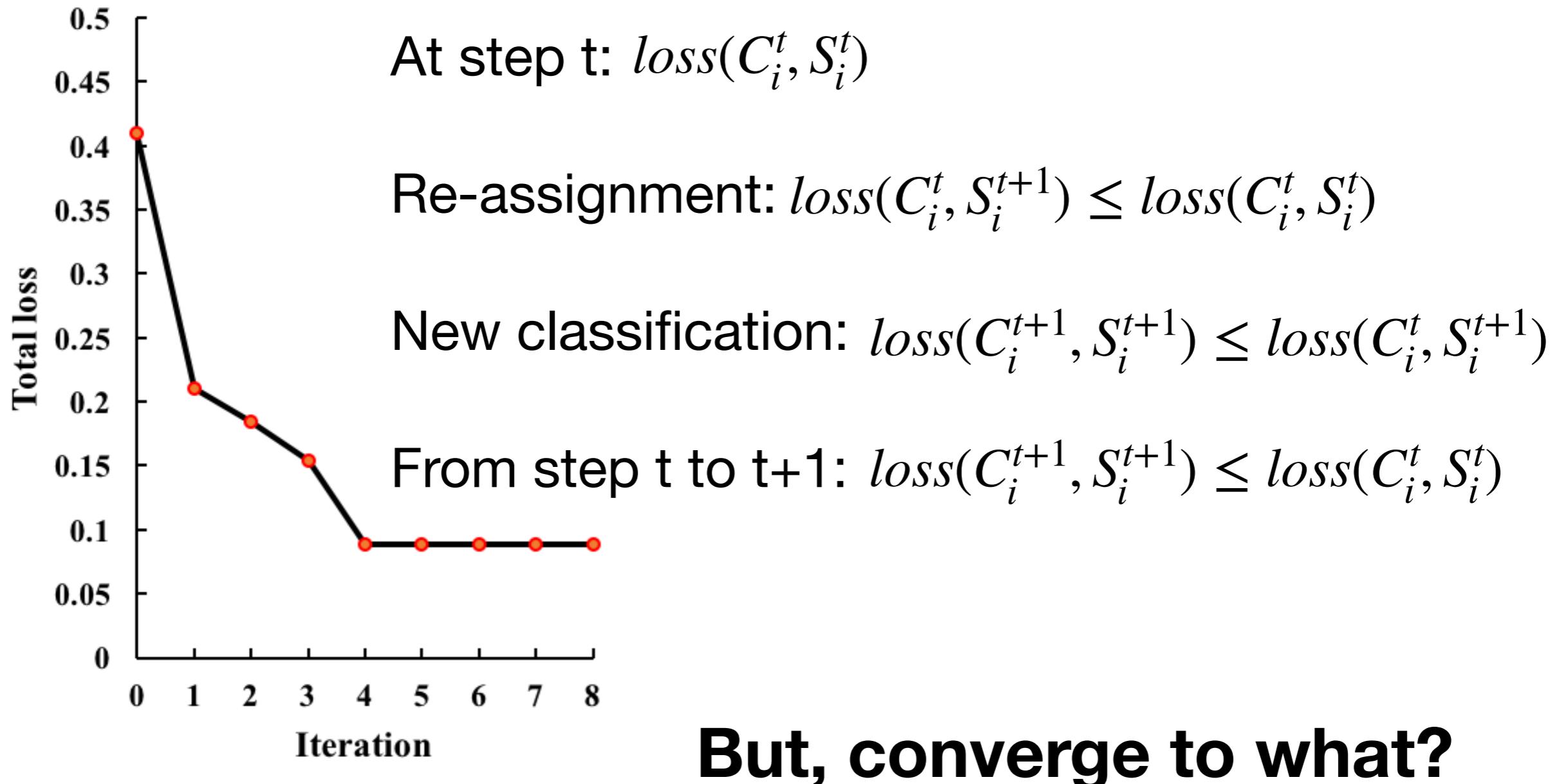


Performances

		Accuracy	Precision	Recall	F – measure	AP	AUC
Synthetic (K=2, M=8)	<i>LR</i>	0.6466 ± 0.07	0.7295 ± 0.05	0.7492 ± 0.14	0.7325 ± 0.07	0.8226 ± 0.03	0.5964 ± 0.08
	<i>SW_{LR}</i>	0.8800 ± 0.06	0.9441 ± 0.05	0.8744 ± 0.08	0.9052 ± 0.05	0.9510 ± 0.03	0.8831 ± 0.06
	<i>KC_{LR}</i>	0.5296 ± 0.16	0.6861 ± 0.15	0.5279 ± 0.16	0.5918 ± 0.15	0.7636 ± 0.10	0.5299 ± 0.17
	PC_{LR}	0.9499 ± 0.05	0.9651 ± 0.03	0.9600 ± 0.05	0.9618 ± 0.04	0.9759 ± 0.02	0.9450 ± 0.05
	<i>SVM</i>	0.7039 ± 0.08	0.8272 ± 0.14	0.7692 ± 0.18	0.7686 ± 0.07	0.8751 ± 0.05	0.6746 ± 0.13
	<i>SW_{SVM}</i>	0.7935 ± 0.10	0.9018 ± 0.12	0.8092 ± 0.16	0.8345 ± 0.10	0.9188 ± 0.05	0.7846 ± 0.14
	<i>KC_{SVM}</i>	0.5873 ± 0.10	0.8630 ± 0.13	0.4834 ± 0.17	0.5897 ± 0.14	0.8444 ± 0.05	0.6367 ± 0.09
	PC_{SVM}	0.9268 ± 0.06	0.9688 ± 0.03	0.9200 ± 0.07	0.9422 ± 0.05	0.9710 ± 0.02	0.9300 ± 0.05
Prod-A (K=5, M=60)	Accuracy	Precision	Recall	F – measure	AP	AUC	
	<i>LR</i>	0.8922 ± 0.01	0.7737 ± 0.02	0.6536 ± 0.03	0.7081 ± 0.03	0.7483 ± 0.02	0.8028 ± 0.01
	<i>SW_{LR}</i>	0.8942 ± 0.01	0.7798 ± 0.03	0.6554 ± 0.03	0.7132 ± 0.02	0.7530 ± 0.02	0.8055 ± 0.01
	<i>KC_{LR}</i>	0.5547 ± 0.13	0.2774 ± 0.20	0.5406 ± 0.06	0.3471 ± 0.14	0.4549 ± 0.12	0.5494 ± 0.10
	PC_{LR}	0.8954 ± 0.01	0.7875 ± 0.05	0.6578 ± 0.04	0.7146 ± 0.03	0.7559 ± 0.03	0.8054 ± 0.02
	<i>SVM</i>	0.8117 ± 0.05	0.5482 ± 0.13	0.5495 ± 0.09	0.5414 ± 0.09	0.5939 ± 0.08	0.7133 ± 0.05
	<i>SW_{SVM}</i>	0.8255 ± 0.04	0.5813 ± 0.12	0.5875 ± 0.10	0.5738 ± 0.08	0.6257 ± 0.07	0.7363 ± 0.04
	<i>KC_{SVM}</i>	0.5399 ± 0.03	0.2222 ± 0.02	0.5194 ± 0.07	0.3108 ± 0.03	0.4188 ± 0.04	0.5322 ± 0.03
	PC_{SVM}	0.8504 ± 0.01	0.6635 ± 0.04	0.5165 ± 0.09	0.5766 ± 0.06	0.6383 ± 0.04	0.7252 ± 0.04
Prod-B (K=3, M=150)	Accuracy	Precision	Recall	F – measure	AP	AUC	
	<i>LR</i>	0.9277 ± 0.01	0.8555 ± 0.01	0.7682 ± 0.05	0.8087 ± 0.03	0.8350 ± 0.02	0.8679 ± 0.02
	<i>SW_{LR}</i>	0.9281 ± 0.01	0.8557 ± 0.01	0.7705 ± 0.05	0.8102 ± 0.03	0.8360 ± 0.02	0.8690 ± 0.02
	<i>KC_{LR}</i>	0.6053 ± 0.12	0.3120 ± 0.19	0.5737 ± 0.04	0.3864 ± 0.12	0.4855 ± 0.11	0.5935 ± 0.08
	PC_{LR}	0.9292 ± 0.00	0.8556 ± 0.01	0.7771 ± 0.02	0.8143 ± 0.01	0.8386 ± 0.01	0.8721 ± 0.01
	<i>SVM</i>	0.8551 ± 0.02	0.6313 ± 0.07	0.7042 ± 0.07	0.6610 ± 0.04	0.6973 ± 0.03	0.7985 ± 0.03
	<i>SW_{SVM}</i>	0.8534 ± 0.03	0.6285 ± 0.07	0.6830 ± 0.09	0.6500 ± 0.06	0.6875 ± 0.05	0.7895 ± 0.04
	<i>KC_{SVM}</i>	0.5346 ± 0.07	0.2259 ± 0.03	0.5347 ± 0.09	0.3157 ± 0.04	0.4268 ± 0.05	0.5346 ± 0.05
	PC_{SVM}	0.8961 ± 0.01	0.7736 ± 0.04	0.6871 ± 0.09	0.7230 ± 0.05	0.7616 ± 0.03	0.8177 ± 0.04

LR: logit regression, SW: segment wised step-by-step method

Converge Analysis



Convex Analysis

- Sub-region generation – K-means
 - Non-convex
 - For n data records, k clusters:
 1. Choose k cluster centers randomly generated in a domain containing all the points
 2. Assign each point to the closest cluster center
 3. Recompute the cluster centers using the current cluster memberships
 4. If a convergence criterion is met, stop; Otherwise go to step 2.

K-means

- Set the assignment matrix: $X = [x_{ij}] \in R^{N \times M}$, if x_i is assigned to T_j then $x_{ij} = 1$, otherwise $x_{ij} = 0$
- For a fixed cluster (sub-region) T_j , cluster center as the mean of all the points in the cluster:

$$\min_c \sum_{i=1}^{|T_j|} \|x_i^{(j)} - c_j\|^2 \Rightarrow c_j = \frac{1}{|T_j|} \sum_{i=1}^{|T_j|} x_i^{(j)}$$

$$\Rightarrow c_j = (\sum_{l=1}^n x_{lj} x_l) / (\sum_{l=1}^n x_{lj})$$

K-means

$$\min_{x_{ij}} \quad \sum_{j=1}^M \sum_{i=1}^N x_{ij} \|x_j - \frac{\sum_{l=1}^n x_{lj} x_l}{\sum_{l=1}^n x_{lj}}\|^2$$

$$s.t. \quad \sum_{j=1}^M x_{ij} = 1, \quad i = 1, \dots, N \text{ each point is assigned to only one cluster}$$

$$\sum_{i=1}^N x_{ij} \geq 1, \quad j = 1, \dots, M \text{ each cluster contains at least one point}$$

$$x_{ij} \in \{0,1\}, \quad i = 1, \dots, N, j = 1, \dots, M$$

Update Step

- Set the assignment matrix: $Z = [z_{jk}] \in R^{M \times K}$; if T_j is assigned to S_k then $x_{jk} = 1$, otherwise $x_{jk} = 0$
- For each segment S_k , a classifier C_k will be trained. If we choose logit regression, C_k could be represented by a sigmoid function $\sigma(\omega, x)$ where

$$\omega = \arg \min \sum_{j=1}^M z_{jk} \sum_{i=1}^N x_{ij} \log[1 + e^{-y \cdot \sigma(\omega^T x)}]$$

Update Step

$$\min_{x_{ij}, z_{jk}} \sum_{k=1}^K \sum_{j=1}^M z_{jk} \sum_{i=1}^N x_{ij} \log[1 + e^{-y \cdot \sigma(\omega^T x)}]$$

$$s.t. \quad \omega = \arg \min \sum_{j=1}^M z_{jk} \sum_{i=1}^N x_{ij} \log[1 + e^{-y \cdot \sigma(\omega^T x)}]$$

$$\sum_{j=1}^M x_{ij} = 1, \quad i = 1, \dots, N; \quad \sum_{i=1}^N x_{ij} \geq 1, \quad j = 1, \dots, M$$

$$\sum_{k=1}^K z_{jk} = 1, \quad j = 1, \dots, M; \quad \sum_{j=1}^M z_{jk} \geq 1, \quad k = 1, \dots, K$$

$$x_{ij}, z_{jk} \in \{0, 1\}, \quad i = 1, \dots, N, \quad j = 1, \dots, M, \quad k = 1, \dots, K$$



Thanks