News Article Classification

(Multi-Label Learning: ML-KNN & BP-MLL)

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Introduction and Problem Statement

KNN Based Approaches

ML-KNN Algorithm: Overall Approach

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&= \underset{b\in\{0,1\}}{\operatorname{argmax}} \frac{\mathbb{P}\left(\mathrm{H}_b^\ell\right) \cdot \mathbb{P}\left(E^\ell_{\vec{C}_{t(\ell)}} | \mathrm{H}_b^\ell\right)}{\mathbb{P}\left(E^\ell_{\vec{C}_t(\ell)}\right)} \\
&= \underset{b\in\{0,1\}}{\operatorname{argmax}} \, \mathbb{P}\left(\mathrm{H}_b^\ell\right) \cdot \mathbb{P}\left(E^\ell_{\vec{C}_{t(\ell)}} | \mathrm{H}_b^\ell\right)
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\end{aligned}
$$

- Where we take a Bayesian approach towards estimating the prior probabilities, $\mathbb{P}\left(\mathrm{H}_b^\ell\right)$, and conditional probabilities, $\mathbb{P}\left(E^\ell_{\vec{C}_{t(\ell)}} | \mathrm{H}_b^\ell\right)$.

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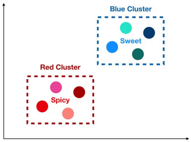
- Let E_j^ℓ $(j \in \{1, ..., K\})$ denote the event that, among the K nearest neighbors of t, there are exactly j instances which have label ℓ.

Data points



Low dimensional space

	Reddish	Bluish
	1	0
	1	0
	1	0
	1	0
	0	1
	0	1
	0	1
	0	1

High dimensional space

	Red	Maroon	Pink	Flamingo	Blue	Turquoise	Seaweed	Ocean
	1	0	0	0	0	0	0	0
	0	1	0	0	0	0	0	0
	0	0	1	0	0	0	0	0
	0	0	0	1	0	0	0	0
	0	0	0	0	1	0	0	0
	0	0	0	0	0	1	0	0
	0	0	0	0	0	0	1	0
	0	0	0	0	0	0	0	1

Having a high dimensional feature space causes Euclidian distances between points to be fairly similar as the distance vector components are partitioned across many dimensions. **?**

Neural Network Based Approaches

Discussion and Conclusions

References