



Mathematical
Institute

Labelling as an unsuper- vised learning problem

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(JOINT WORK WITH T. LYONS)

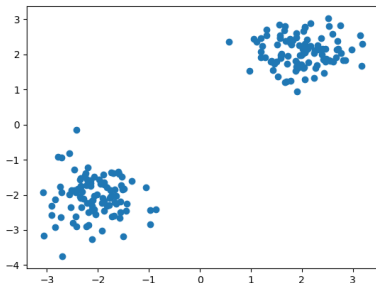
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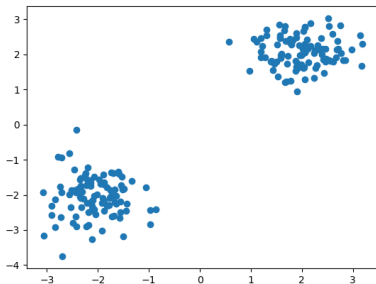
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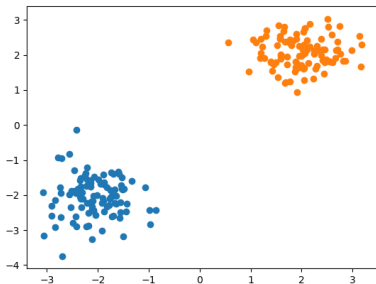
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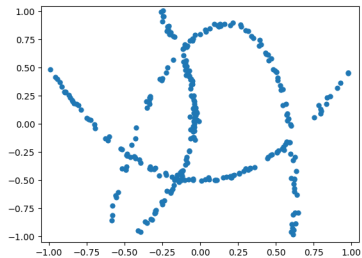
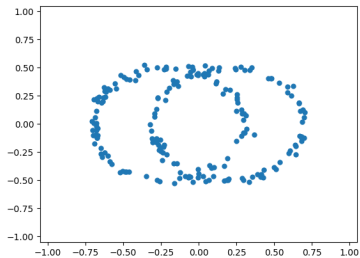
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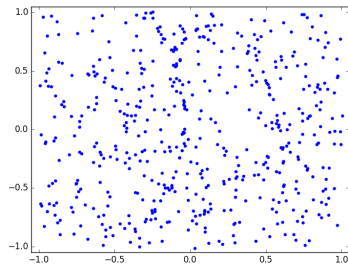
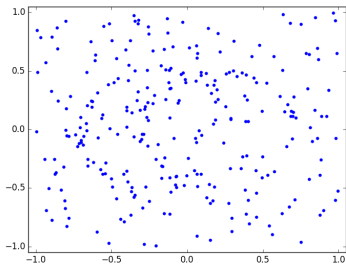
- ▶ An approach one could follow is to *cluster* the data, i.e. find a suitable partition of the dataset.



Unsupervised learning



Unsupervised learning



- ▶ A cloud of points will share a label if unreasonably many of them share a common relationship.
- ▶ Points may have one, multiple or no labels.

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- ▶ The μ -augmented observation space is defined as the tuple $(\mathcal{X}, F, \Phi, \mu)$.

Example (Polynomials in several variables)

In the case where the observation space is \mathbb{R}^d , we can define an augmented observation space by considering the feature map given by the mapping to a basis of polynomials of fixed degree.

Example (Path space)

If $\mathcal{X} = \mathcal{V}^1([0, T]; \mathbb{R}^d)$, we can define an augmented observation space using the signature map as the feature map.

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Definition (Label)

Let $(\mathcal{X}, F, \Phi, \mu)$ be a μ -augmented observation space, let $\mathcal{C} \subset \mathcal{X}$ and set $0 < \delta < 1$. A potential label $f \in \mathcal{F}_\Phi$ is called a (μ, δ) -label for \mathcal{C} if there exists an interval $I \subset \mathbb{R}$ such that $0 \in I$, $f(\mathcal{C}) \subset I$ and

$$(f_*(\mu))(I) < \delta,$$

where $f_*(\mu)$ is the pushforward measure defined as $(f_*(\mu))(I) := \mu(f^{-1}(I))$.

Definition

Let $(\mathcal{X}, F, \Phi, \mu)$ be a μ -augmented observation space, $\mathcal{C} \subset \mathcal{X}$ and $0 < \delta < 1$. The set of labels for \mathcal{C} is defined as

$$\mathcal{L}_{\mu, \delta}(\mathcal{C}) := \{f \in \mathcal{F}_{\Phi} : f \text{ is a } (\mu, \delta)\text{-label for } \mathcal{C}\}.$$

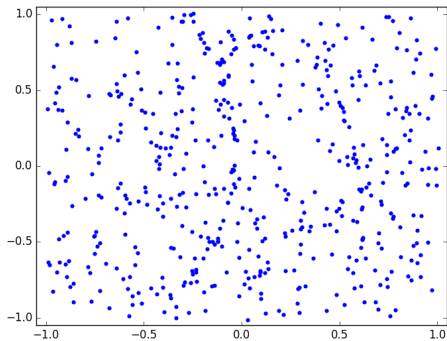
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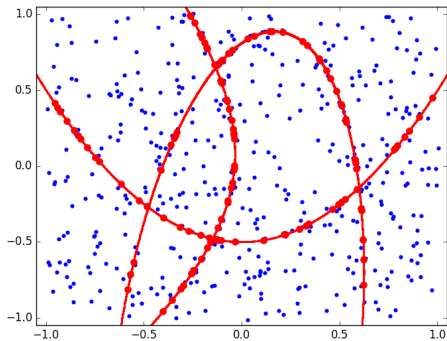
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- ▶ If $f \in \mathcal{F}_\Phi$ is a (μ, δ) -label, then λf is a (μ, δ) -label for all $\lambda \in \mathbb{R} \setminus \{0\}$.
- ▶ However, $\mathcal{L}_{\mu,\delta}(\mathcal{C})$ is not a vector space in general.

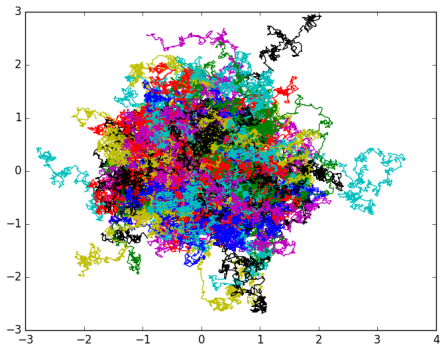
Examples



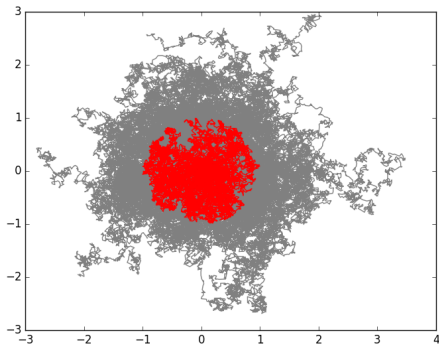
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Label: $f(X) = \max_t |X_t| - 1$.

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- ▶ How does this depend on the sample size? And on δ , the feature map or the background noise?

-
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- ▶ Define the linear compact operator

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- ▶ We want to study what is the probability that there exists $l \in F'$ such that $\{\langle l, \Phi(X) \rangle\}_{X \in \mathcal{C}}$ is contained in a *small* interval.
- ▶ Thus, we have to study the spectrum of the random matrix Γ_Φ .

Theorem

Let $(\mathcal{X}, F, \Phi, \mu)$ be a μ -augmented observation space, with \mathcal{X} a Banach space. Assume that

- (i) $\mathbb{E}_\mu(\Phi(X)^* \Phi(X)) = I$.
- (ii) $\|\Phi(x)\|_F \leq 1 + \|x\|_{\mathcal{X}}^k$, for all $x \in \mathcal{X}$, where $k > 0$.
- (iii) $\mathbb{P}_\mu(\|\Phi(X)\|_F > \lambda) \lesssim \exp(-C\lambda^\alpha)$, where $\alpha \geq k$.

Then, $s_{\min}(\Gamma_\Phi) \sim \sqrt{|\mathcal{C}|}$ with probability higher than $1 - \exp(-p_{D,|\mathcal{C}|})$, with $p_{D,|\mathcal{C}|} \xrightarrow{|\mathcal{C}| \rightarrow \infty} \infty$.

Theorem (Probability of false discovery)

Let $(\mathcal{X}, F, \Phi, \mu)$ be a μ -augmented observation space and let $\mathcal{C} \subset \mathcal{X}$ be a finite set of points independently distributed according to μ . Assume that the feature map satisfies the assumptions of the previous theorem.

Then, give any $\epsilon > 0$, there exists $\delta_{\epsilon, |\mathcal{C}|} > 0$ such that the probability that there exists a $(\mu, \delta_{\epsilon, |\mathcal{C}|})$ -label for \mathcal{C} is less than $(C/\epsilon)^D \exp(-p_{D, |\mathcal{C}|})$, with $C > 0$ a constant.

Proof (sketch)

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We want to estimate:

$$\mathbb{P}_\mu(\exists (\mu, \delta) - \text{label for } \mathcal{C}) = \mathbb{P}_\mu \left(\bigvee_{f \in \mathcal{F}_\Phi} f \text{ is a } (\mu, \delta) - \text{label for } \mathcal{C} \right)$$

- ▶ Obtain estimates for $\mathbb{P}_\mu(f \text{ is a } (\mu, \delta) - \text{label for } \mathcal{C})$, for a fixed $f \in \mathcal{C}$.
- ▶ Use an ϵ -net argument to restrict \mathcal{F}_Φ to some finite subset.

Lyons, T. and Perez Arribas, I. "Labelling as an unsupervised learning problem." *ArXiv:1805.03911 (2018)*.