

# Robust Linear Regression by Subquantile Minimization

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# Presentation Overview

## ① Robust Regression

- Huber Contamination Model
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# Huber Contamination Model

## Problem

The *Huber Contamination Model* is the following:

$$\hat{P} = (1 - \varepsilon)P + \varepsilon Q \text{ where } \varepsilon \in (0, 0.5)$$

where  $P$  and  $Q$  represent the general linear models

$$\mathbf{y}_P = \boldsymbol{\beta}_P^\top \mathbf{P} + \epsilon_P$$

$$\mathbf{y}_Q = \boldsymbol{\beta}_Q^\top \mathbf{Q} + \epsilon_Q$$

$\boldsymbol{\beta}_P$  and  $\boldsymbol{\beta}_Q$  are oracle regressors and  $\epsilon_P$  and  $\epsilon_Q$  represent 0-centered gaussian noise.

Our goal is to learn a model that learns a good distribution of  $P$  from  $\hat{P}$

# Motivation

## Definition

Oblivious Noise is noise which is independent of the input data

Adaptive Noise is noise which is dependent upon the input data

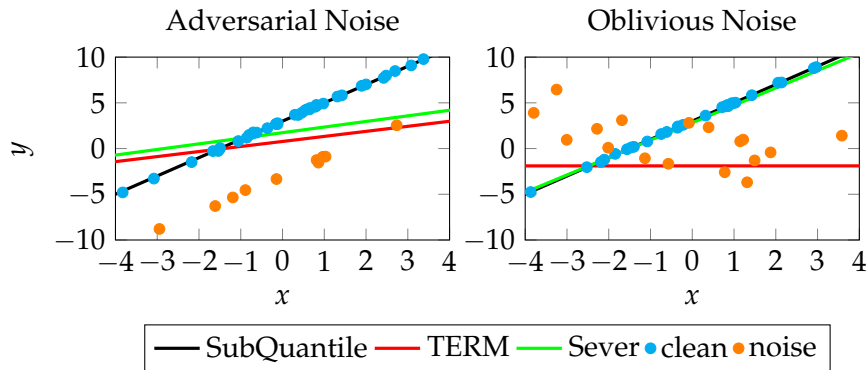


Figure: Sub-Quantile Performance on Adaptive Outliers

## Theorem

The expected optimal parameters of the corrupted model  $\hat{P}$

$$\mathbb{E} \left[ \mathbf{X}^\dagger \mathbf{y} \right] = (1 - \varepsilon) \boldsymbol{\beta}_P + \varepsilon \boldsymbol{\beta}_Q$$

where  $\mathbf{X}^\dagger \triangleq (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top$ , i.e. the Moore-Penrose Inverse.

This theorem motivates our reasoning for optimizing over the Subquantile. We want a method to reduce  $\varepsilon$ .

# Statistical Preliminaries of the Subquantile

1

$$\mathcal{Q}_p = \inf \{x \in \mathbb{R} : p \leq F(x)\}$$

2 Let  $\ell$  be the loss functions. We can now define risk as:

$$\mathcal{U} = \mathbb{E} [\ell(f(\mathbf{x}; \boldsymbol{\theta}), y)]$$

3 The  $p$ -Quantile of the Empirical Risk is given by:

$$\mathbb{L}_p = \frac{1}{p} \int_0^p \mathcal{Q}_q(\mathcal{U}) dq = \mathbb{E} [\mathcal{U} | \mathcal{U} \leq \mathcal{Q}_p(\mathcal{U})] = \max_{t \in \mathbb{R}} \left\{ t - \frac{1}{p} \mathbb{E} [(t - \mathcal{U})^+] \right\}$$

4 For the least squares regression case:

$$\mathbb{L}_p = \max_{t \in \mathbb{R}} \left\{ t - \frac{1}{np} \sum_{i=1}^n \left( t - (\boldsymbol{\theta}^\top \mathbf{x}_i - y_i) \right)^+ \right\}$$

# Multiple Columns

Subtitle

## Heading

- ① Statement
- ② Explanation
- ③ Example

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| Objectives                        | Test RMSE (Drug Discovery)       |                                  |                                  |                                  |
|-----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|
|                                   | $\epsilon = 0.1$                 | $\epsilon = 0.2$                 | $\epsilon = 0.3$                 | $\epsilon = 0.4$                 |
| ERM                               | 1.303 <sub>(0.0665)</sub>        | 1.790 <sub>(0.0849)</sub>        | 2.198 <sub>(0.0645)</sub>        | 2.623 <sub>(0.1010)</sub>        |
| CRR [?]                           | <b>1.079</b> <sub>(0.0899)</sub> | 1.125 <sub>(0.0832)</sub>        | 1.385 <sub>(0.1372)</sub>        | 1.725 <sub>(0.1136)</sub>        |
| STIR [?]                          | 1.087 <sub>(0.1256)</sub>        | 1.167 <sub>(0.0750)</sub>        | 1.403 <sub>(0.0987)</sub>        | 1.668 <sub>(0.1142)</sub>        |
| Robust Risk [?]                   | 1.176 <sub>(0.1110)</sub>        | 1.336 <sub>(0.1882)</sub>        | 1.437 <sub>(0.1723)</sub>        | 1.800 <sub>(0.0820)</sub>        |
| SMART [?]                         | 1.094 <sub>(0.1065)</sub>        | 1.323 <sub>(0.0758)</sub>        | 1.578 <sub>(0.0799)</sub>        | 1.984 <sub>(0.2020)</sub>        |
| TERM [?]                          | 1.326 <sub>(0.0757)</sub>        | 1.357 <sub>(0.0990)</sub>        | 1.310 <sub>(0.0670)</sub>        | 1.302 <sub>(0.0851)</sub>        |
| SEVER [?]                         | 1.111 <sub>(0.0924)</sub>        | <b>1.067</b> <sub>(0.0457)</sub> | <b>1.071</b> <sub>(0.0807)</sub> | <b>1.138</b> <sub>(0.1162)</sub> |
| Huber [?]                         | 1.412 <sub>(0.0474)</sub>        | 1.501 <sub>(0.2918)</sub>        | 2.231 <sub>(0.9054)</sub>        | 2.247 <sub>(1.0399)</sub>        |
| RANSAC [?]                        | 1.238 <sub>(0.0529)</sub>        | 1.643 <sub>(0.1331)</sub>        | 2.092 <sub>(0.1935)</sub>        | 2.679 <sub>(0.1365)</sub>        |
| SubQuantile( $p = 1 - \epsilon$ ) | <b>0.887</b> <sub>(0.1046)</sub> | <b>0.936</b> <sub>(0.1051)</sub> | <b>0.927</b> <sub>(0.0729)</sub> | <b>1.015</b> <sub>(0.0978)</sub> |
| Genie ERM                         | 0.986 <sub>(0.1039)</sub>        | 0.955 <sub>(0.0698)</sub>        | 1.038 <sub>(0.0886)</sub>        | 1.030 <sub>(0.0578)</sub>        |

**Table:** Drug Discovery Dataset. Empirical Risk over  $P$  with oblivious noise





# Rensselaer

# Definitions & Examples

## Definition

A **prime number** is a number that has exactly two divisors.

## Example

- 2 is prime (two divisors: 1 and 2).
- 3 is prime (two divisors: 1 and 3).
- 4 is not prime (**three** divisors: 1, 2, and 4).

You can also use the theorem, lemma, proof and corollary environments.

# Theorem, Corollary & Proof

Theorem (Mass–energy equivalence)

$$E = mc^2$$

Corollary

$$x + y = y + x$$

Proof.

$$\omega + \phi = \epsilon$$



# Equation

$$\cos^3 \theta = \frac{1}{4} \cos \theta + \frac{3}{4} \cos 3\theta \quad (1)$$

## Example (Theorem Slide Code)

```
\begin{frame}  
\frametitle{Theorem}  
\begin{theorem}[Mass--energy equivalence]  
$E = mc^2$  
\end{theorem}  
\end{frame}
```

Slide without title.

An example of the `\cite` command to cite within the presentation:

This statement requires citation [Smith, 2022, Kennedy, 2023].

# References



John Smith (2022)

Publication title

*Journal Name* 12(3), 45 – 678.



Annabelle Kennedy (2023)

Publication title

*Journal Name* 12(3), 45 – 678.



# Acknowledgements

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# The End

Questions? Comments?