Universitat Politècnica de Catalunya (UPC) – BarcelonaTech

DEGREE FINAL PROJECT

Using Random Fourier Features with Random Forest

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Computer Science

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UNIVERSITAT POLITÈCNICA DE CATALUNYA (UPC) – BARCELONATECH

Abstract

Facultat d'Informàtica de Barcelona (FIB) Computer Science

Bachelor Degree in Computer Science

Using Random Fourier Features with Random Forest

by Albert RIBES

The Thesis Abstract is written here (and usually kept to just this page). The page is kept centered vertically so can expand into the blank space above the title too...

• En 3 idiomas

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List of Abbreviations

ML Machine Learning

SVM Support Vector Machine RBF Radial Basis Function

DT Decision Tree RF Random Forest

RFF Random Fourier Features

CV Cross-Validation

Introduction

1.1 Problem to solve

Trade-off between accuracy and train time is not good

1.2 Why is it important?

- Avances en este campo permitirían usarlo en otras ciencias como medicina, economía, sociedad
- Muchas tareas que ahora tiene que hacer un humano podría hacerlas una máquina, ahorrando tiempo y dinero

1.3 Project proposal

- Existe una batería de técnicas que son buenas, pero que nadie las ha combinado. Son:
 - Modelos simples
 - Ensembles
 - kernel trick
 - Aproximaciones de kernel
- La propuesta es combinar todo esto para mejorar el trade-off
- Sostenemos las siguientes hipótesis:
 - Se podría hacer un ensemble con modelos distintos a DT
 - Se puede aproximar una RBF-SVM pero con el coste de una lineal
 - RFF + Bootstrap quizá es demasiado aleatorio
 - Los modelos que no se basan en productos escalares no se beneficiarán tanto de usar RFF
- Lo que se hará en cada capítulo del trabajo

Background Information and Theory

2.1 Machine Learning

- Una definición rápida
- Clasificación y regresión
- Cross-validation
- Qué son los datos de train y test, y por qué se hace esa partición
- Qué es el sobre-ajuste

2.2 Review de los principales modelos que existen

2.2.1 Decision Tree

- No se basa en productos escalares
- Es extremadamente rápido
- Es más fácil de interpretar que otros modelos
- Es extremadamente inestable
- Cuando se hace un Random Forest, se randommiza un poco, de modo que árboles distintos entrenados con los mismos datos pueden ser destintos
- Es un modelo no lineal

2.2.2 Logistic Regression

Hola que tal

2.2.3 Support Vector Machines

- Inicialmente pensadas para clasificación en 2 clases
- Pero se puede más clases con *one-vs-rest* y también hay formas de hacer regresión
- Se basa únicamente en el producto escalar de sus entradas
- Intenta separar los datos con un híper-plano
- Actualmente es poco eficiente usarlas porque su coste s cúbico con la cantidad de entradas.
- Las fórmulas que quiere optimizar

2.3 Ensemble Methods

- Bagging
 - Inventado por Leo Breiman (referencia)
 - Pretende reducir el sesgo
 - Entrenamiento de los estimadores es independiente, se podría hacer en paralelo
 - Actualmente casi solo se usa con DT, debido a su inestabilidad
- Bootstrap
 - Intenta solucionar el problema de que para bagging es bueno que los estimadores sean distintos
 - Idealmente usaríamos un dataset distinto para cada estimador
 - Consiste en hacer un resalmpling con repetición
 - Si la cantidad de instancias del original es la misma que la de cada uno de los subconjuntos, se espera que la proporción de elementos úncos sea de $1-\frac{1}{a}\approx 0.632$.
 - Si el conjunto original tiene n elementos, y tu haces un subconjunto de tamaño r, puedes esperar que la proporción de elementos del original que sí tienen presencia en el nuevo sea de $1-e^{-\frac{r}{n}}$
- Random Forest

2.4 The kernel trick

- Teorema de Bochner
- El kernel RBF
 - Su fórmula es ...

- Equivalencia entre γ y σ
- La noción de similitud que tiene
- \mathcal{H} es de dimensionalidad infinita
- Permite ajustarse infinitamente a los datos, tuneando el híperparámetro
- $-\sigma$ más pequeño, más sobreajuste
- $-\gamma$ más grande, más sobreajuste

2.5 Random Fourier Features

2.6 Nyström

Project Development

3.1 General Idea

- Hemos visto que se puede sacar una aproximación aleatoria de la función implícita de un shift invariant kernel. Esto tiene 2 ventajas
 - Podemos transformar los datos directamente
 - Podemos producir pequeñas variaciones de un mismo dataset, todas ellas válidas
- Las 4 tipos de modelos que he definido. Referencia a la foto
- ¿Por qué he cogido estos 4 modelos? ¿No podrían haber sido otros? ¿Que tienen estos de bueno? Me he inspirado en Random Forest
- Hay por ahí algún paper que compara RFF y Nyström

3.1.1 State of the art con las RFF

- Se ha trabajado poco con ellas. Solo he encontrado 2 usos:
 - Stacked kernel network (referencia): usarlas junto a una red neuronal para tener más niveles de aprendizaje no lineal
 - RFF with SVM (referencia): usar una SVM sin kernel con los datos mapeados usando RFF

3.1.2 State of the art con las Nyström

3.2 Hyper-parameters

- Existen los siguientes:
 - min-impurity-decrease para DT
 - C para SVM
 - gamma para RFF y Nyström
 - cantidad de features para RFF y Nyström

- cantidad de estimadores para ensembles
- Hemos usado los siguientes valores:
 - Cantidad de features a 500
 - Cantidad de estimadores a 50
 - En modelos simples, el parámetro por crossvalidation
 - En modelos simples con RFF, el parámetro por crossvalidation y una gamma que sobreajuste
 - En modelos con ensemble, parámetros que sobreajusten y la gamma por crossvalidation
 - En RBF-SVM, la gamma por gamest y el parámetro por crossvalidation

3.3 Hypothesis

- 1. Podemos aproximar bien una RBF-SVM
- 2. Puede tener sentido hacer ensembles con otros modelos a DT
- 3. RFF + Bootstrap puede ser malo
- 4. Si el modelo no se basa en productos escalares no se feneficiará tanto

3.3.1 Planteamiento de los experimentos

- 1. Hipótesis: Aproximar RBF-SVM
 - 1.1. Comparar una RBF-SVM con SVM normal que use RFF
- 2. Hipótesis: Ensembles con otros
 - 2.1. Logit normal vs. Logit con RFF
 - 2.2. Logit normal vs. Logit con RFF Black Bag
 - 2.3. Logit normal vs. Logit con RFF Grey Bag
 - 2.4. Logit normal vs. Logit con RFF Grey Ensemble
 - 2.5. Linear-SVM vs Linear-SVM con RFF
 - 2.6. Linear-SVM vs Linear-SVM con RFF Black Bag
 - 2.7. Linear-SVM vs Linear-SVM con RFF Grey Bag
 - 2.8. Linear-SVM vs Linear-SVM con RFF Grey Ensemble
- 3. Hipótesis: RFF + Bootstrap
 - 3.1. Logit con RFF Grey Bag vs Logit con RFF Grey Ensemble
 - 3.2. Logit con RFF Black Bag vs Logit con RFF Black Ensemble (los dos con un solo estimador)

3.4. Datasets 9

- 3.3. Linear-SVM con RFF Grey Bag vs Linear-SVM con RFF Grey Ensemble
- 3.4. Linear-SVM con RFF Black Bag vs Linear-SVM con RFF Black Ensemble (los
- 4. Hipótesis: DT + RFF
 - DT vs DT con RFF
 - DT vs DT con RFF Black Bag
 - DT vs DT con RFF Black Ensemble
 - DT vs DT con RFF Grey Bag
 - DT vs DT con RFF Grey Ensemble

3.4 Datasets

- 8 Datasets
- Normalizados
- Únicamente tienen variables numéricas, no categóricas
- Únicamente problemas de clasificación
- Algunas cosas particulares que he hecho:
 - Mezclar datos de train y de test para luego hacer mi propia separación
 - Cuando había poca presencia de una clase, hacer un resampling para igualar las cantidades
 - No trabajar cosas como el skiwness o los outliers
 - Eliminar columnas en las que todo eran 0
 - Reducir el conjunto de instancias

Experimental Results

- 4.1 Enfrentar resultados 2 a 2
- 4.2 Contrastar hipótesis con resultados

Conclusion and Future Directions

- Problemas de regresión
- Aproximar otros kernels a RBF
- Ver el comportamiento con problemas que no sean tan bonitos (con missings, clases desbalanceadas, etc)
- Otros tipos de ensembles, como el boosting

Sustainability Report

- 6.1 Environmental
- 6.2 Economic
- 6.3 Social
 - 6.3.1 Impacto Personal
 - 6.3.2 Impacto Social
 - 6.3.3 Riesgos Sociales

Appendix A

Results of experiment 1.1

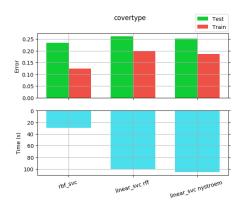


FIGURE A.1: RBF-SVM and Linear-SVM with RFF and Nyström

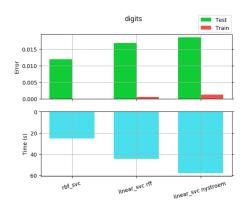


FIGURE A.2: RBF-SVM and Linear-SVM with RFF and Nyström

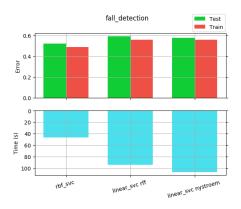


FIGURE A.3: RBF-SVM and Linear-SVM with RFF and Nyström

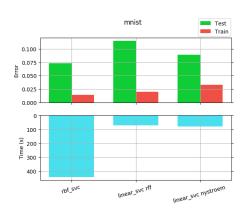


FIGURE A.4: RBF-SVM and Linear-SVM with RFF and Nyström

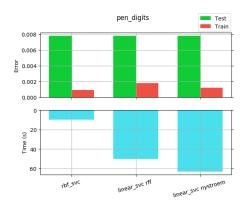


FIGURE A.5: RBF-SVM and Linear-SVM with RFF and Nyström

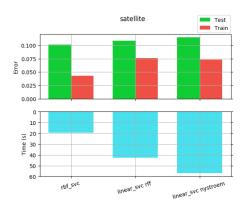


FIGURE A.6: RBF-SVM and Linear-SVM with RFF and Nyström

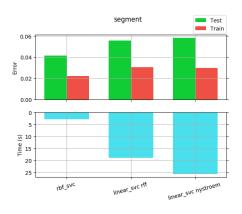


FIGURE A.7: RBF-SVM and Linear-SVM with RFF and Nyström

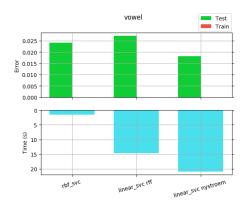
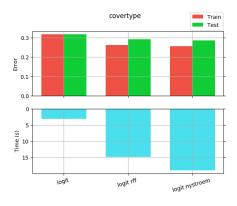


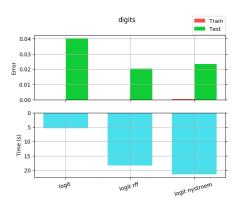
FIGURE A.8: RBF-SVM and Linear-SVM with RFF and Nyström

Appendix B

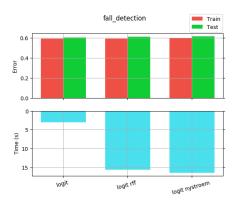
Results of experiment 2.1



 $\label{eq:Figure B.1: Normal Logistic Regression} \ and \ with RFF \ and \ Nystr\"{o}m$



 $\label{eq:Figure B.2: Normal Logistic Regression and with RFF and Nyström$



 $\label{eq:Figure B.3: Normal Logistic Regression and with RFF and Nyström$

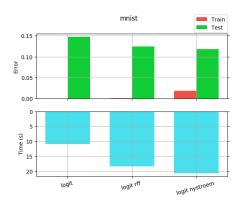


FIGURE B.4: Normal Logistic Regression and witdh RFF and Nyström

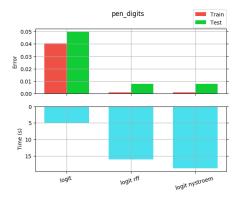


FIGURE B.5: Normal Logistic Regression and witdh RFF and Nyström $\,$

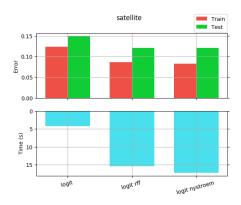


FIGURE B.6: Normal Logistic Regression and witdh RFF and Nyström $\,$

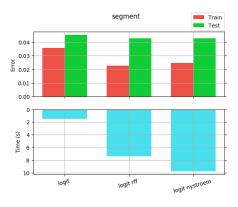


Figure B.7: Normal Logistic Regression and withh RFF and Nyström $\,$

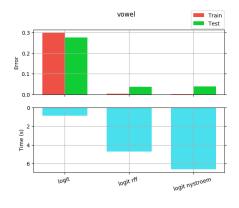


FIGURE B.8: Normal Logistic Regression and witdh RFF and Nyström $\,$

Appendix C

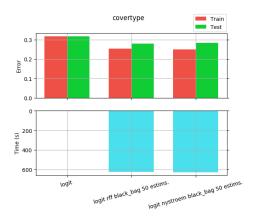


FIGURE C.1: Logistic Regression with Black Bag model

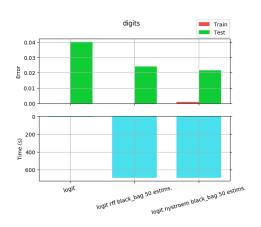


FIGURE C.2: Logistic Regression with Black Bag model

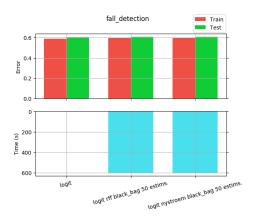


FIGURE C.3: Logistic Regression with Black Bag model

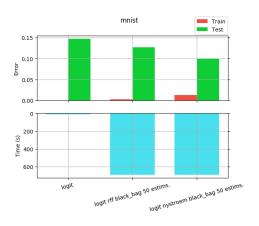


FIGURE C.4: Logistic Regression with Black Bag model

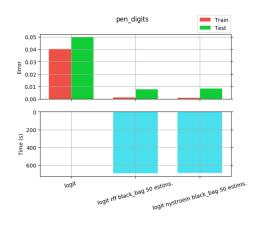


FIGURE C.5: Logistic Regression with Black Bag model

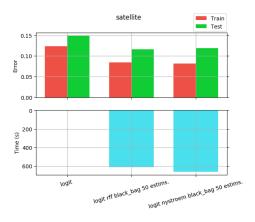


FIGURE C.6: Logistic Regression with Black Bag model

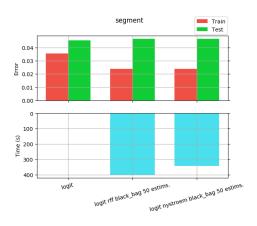


FIGURE C.7: Logistic Regression with Black Bag model

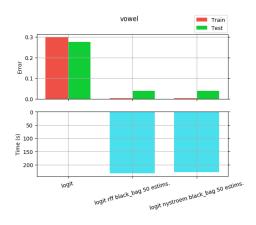


FIGURE C.8: Logistic Regression with Black Bag model

Appendix D

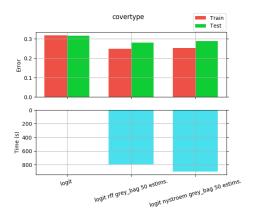


FIGURE D.1: Logistic Regression with Grey Bag model

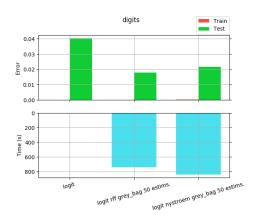


FIGURE D.2: Logistic Regression with Grey Bag model

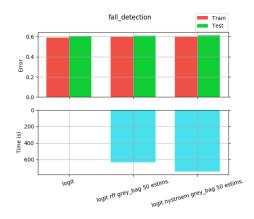


FIGURE D.3: Logistic Regression with Grey Bag model

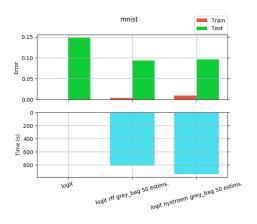


FIGURE D.4: Logistic Regression with Grey Bag model

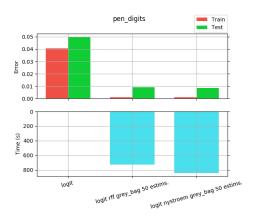


FIGURE D.5: Logistic Regression with Grey Bag model

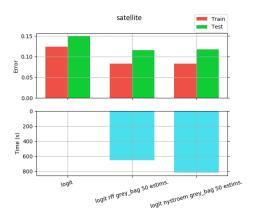


FIGURE D.6: Logistic Regression with Grey Bag model

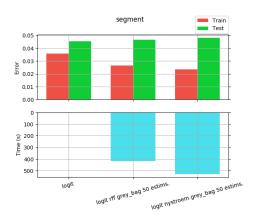


FIGURE D.7: Logistic Regression with Grey Bag model

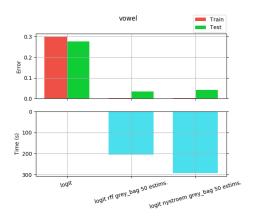


FIGURE D.8: Logistic Regression with Grey Bag model

Appendix E

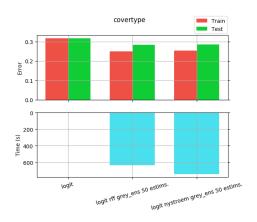


FIGURE E.1: Logistic Regression with Grey Ensemble model

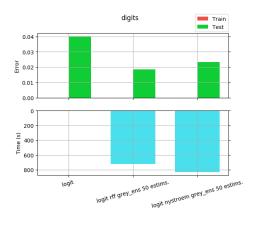


FIGURE E.2: Logistic Regression with Grey Ensemble model

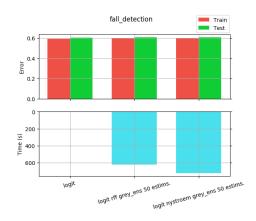


FIGURE E.3: Logistic Regression with Grey Ensemble model

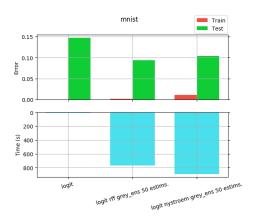


FIGURE E.4: Logistic Regression with Grey Ensemble model

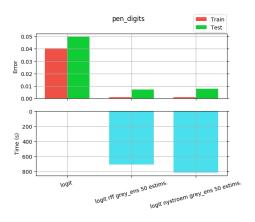


FIGURE E.5: Logistic Regression with Grey Ensemble model

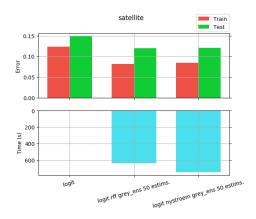


FIGURE E.6: Logistic Regression with Grey Ensemble model

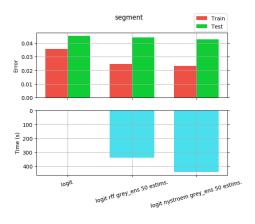


FIGURE E.7: Logistic Regression with Grey Ensemble model

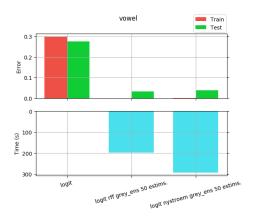


FIGURE E.8: Logistic Regression with Grey Ensemble model

Appendix F

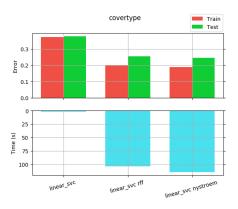


FIGURE F.1: Linear-SVC with RFF and Nyström

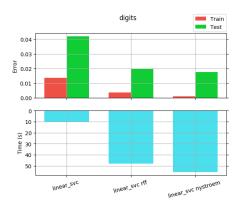


FIGURE F.2: Linear-SVC with RFF and Nyström

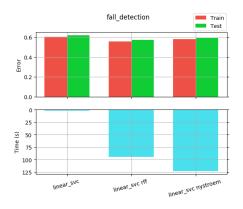


FIGURE F.3: Linear-SVC with RFF and Nyström

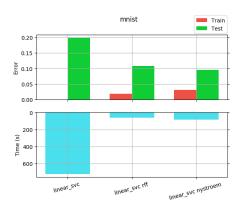


FIGURE F.4: Linear-SVC with RFF and Nyström

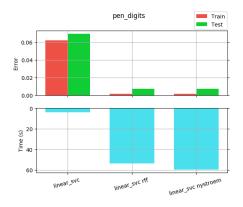


FIGURE F.5: Linear-SVC with RFF and Nyström

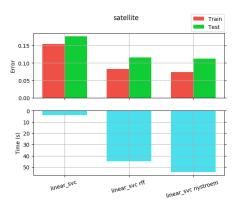


FIGURE F.6: Linear-SVC with RFF and Nyström

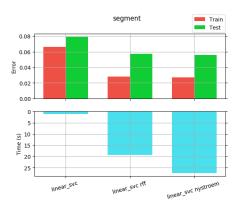


FIGURE F.7: Linear-SVC with RFF and Nyström

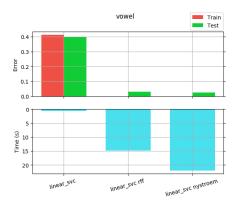


FIGURE F.8: Linear-SVC with RFF and Nyström

Appendix G

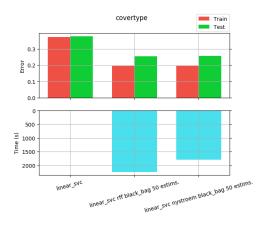


FIGURE G.1: Linear-SVM with Black Bag model

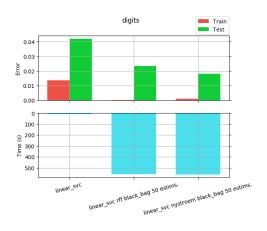


FIGURE G.2: Linear-SVM with Black Bag model

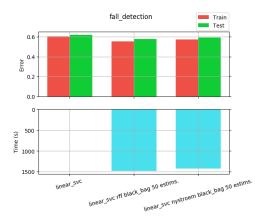


FIGURE G.3: Linear-SVM with Black Bag model

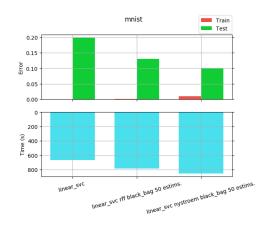


FIGURE G.4: Linear-SVM with Black Bag model

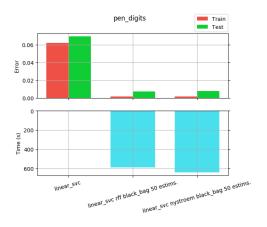


Figure G.5: Linear-SVM with Black Bag model

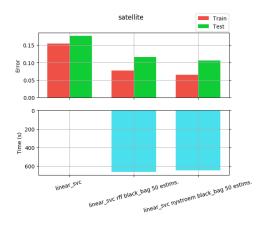


FIGURE G.6: Linear-SVM with Black Bag model

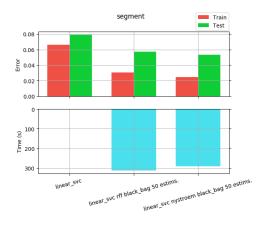
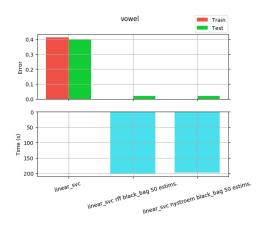


FIGURE G.7: Linear-SVM with Black Bag model



 $FIGURE\ G.8:\ Linear-SVM\ with\ Black\ Bag\ model$

Appendix H

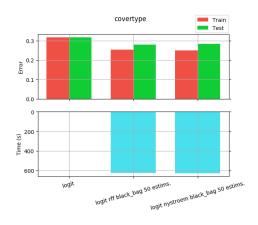


FIGURE H.1: Logistic Regression with Black Bag model

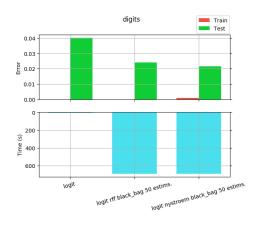


FIGURE H.2: Logistic Regression with Black Bag model

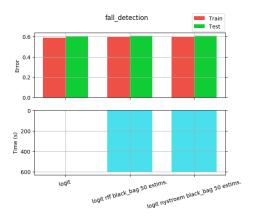


FIGURE H.3: Logistic Regression with Black Bag model

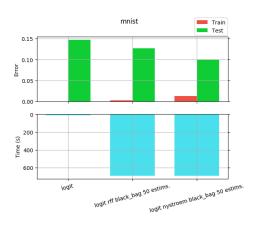


FIGURE H.4: Logistic Regression with Black Bag model

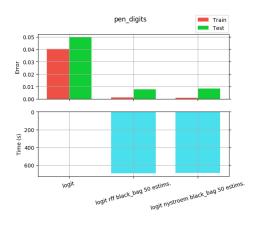


FIGURE H.5: Logistic Regression with Black Bag model

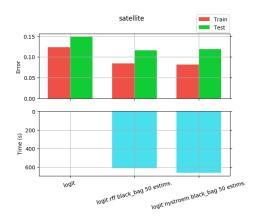


FIGURE H.6: Logistic Regression with Black Bag model

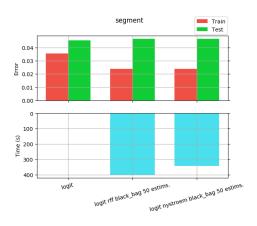


FIGURE H.7: Logistic Regression with Black Bag model

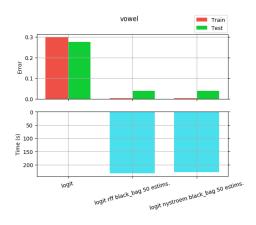


FIGURE H.8: Logistic Regression with Black Bag model

Appendix I

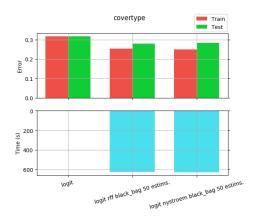


FIGURE I.1: Logistic Regression with Black Bag model

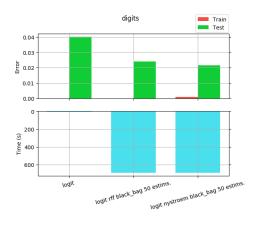


FIGURE I.2: Logistic Regression with Black Bag model

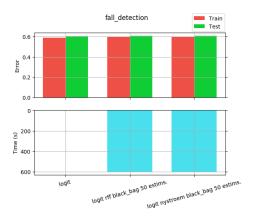


FIGURE I.3: Logistic Regression with Black Bag model

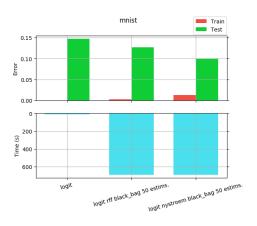


FIGURE I.4: Logistic Regression with Black Bag model

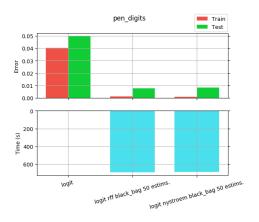


FIGURE I.5: Logistic Regression with Black Bag model

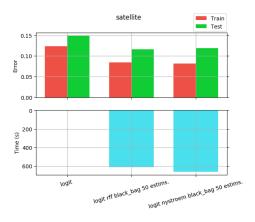


FIGURE I.6: Logistic Regression with Black Bag model

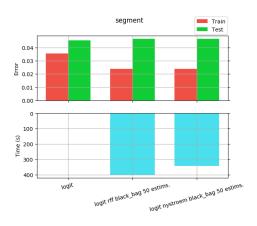


FIGURE I.7: Logistic Regression with Black Bag model

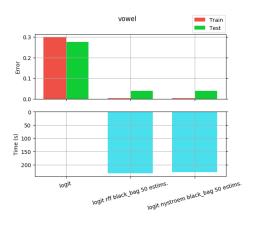


FIGURE I.8: Logistic Regression with Black Bag model