Bayesian Methods for Parkinson's disease prediction

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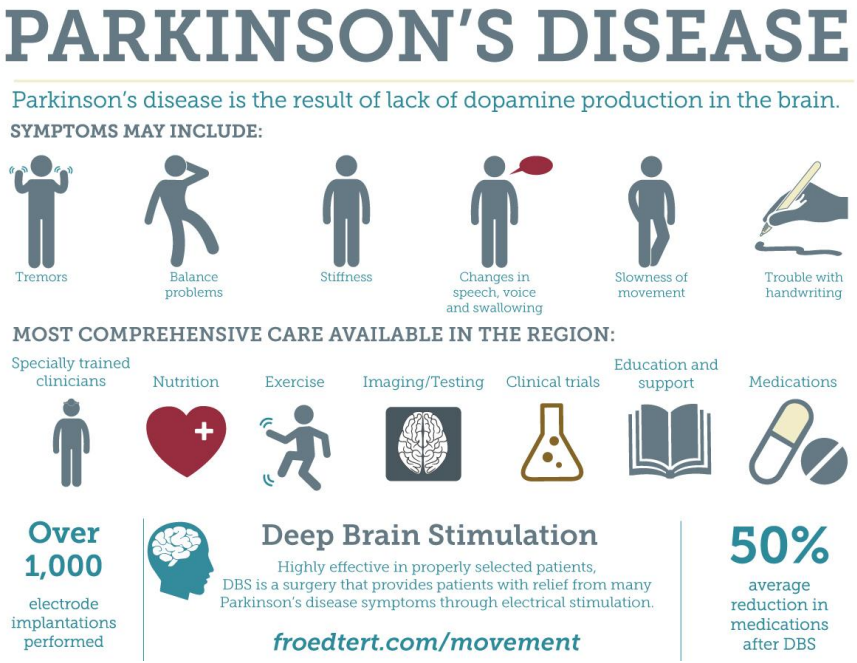
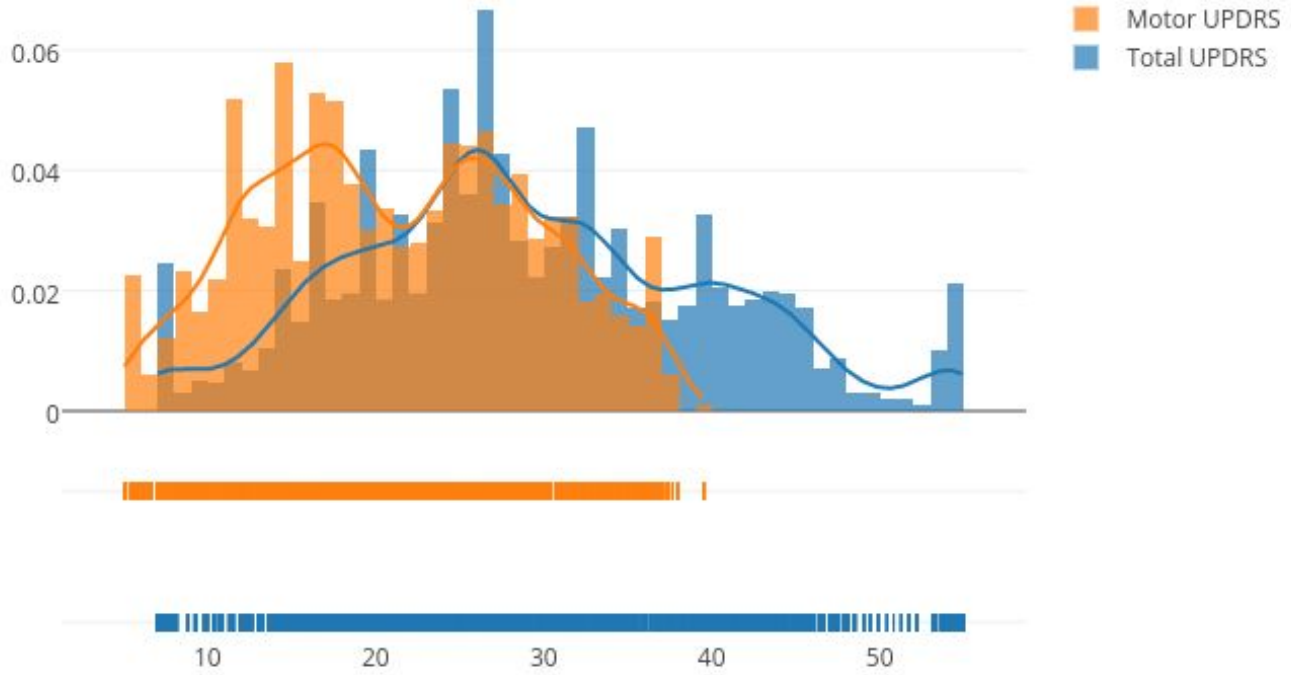
Introduction

- Approximately 90% of patients diagnosed with Parkinson's disease exhibit some form of vocal impairment
- Evidence suggests that vocal impairment may be one of the earliest indicators for the onset of the disorder
- Using voice measurement to detect and track the progression of symptoms of Parkinson's has been a key focus for researchers
- However computational analysis of this data is novel



The Parkinsons Telemonitoring Dataset

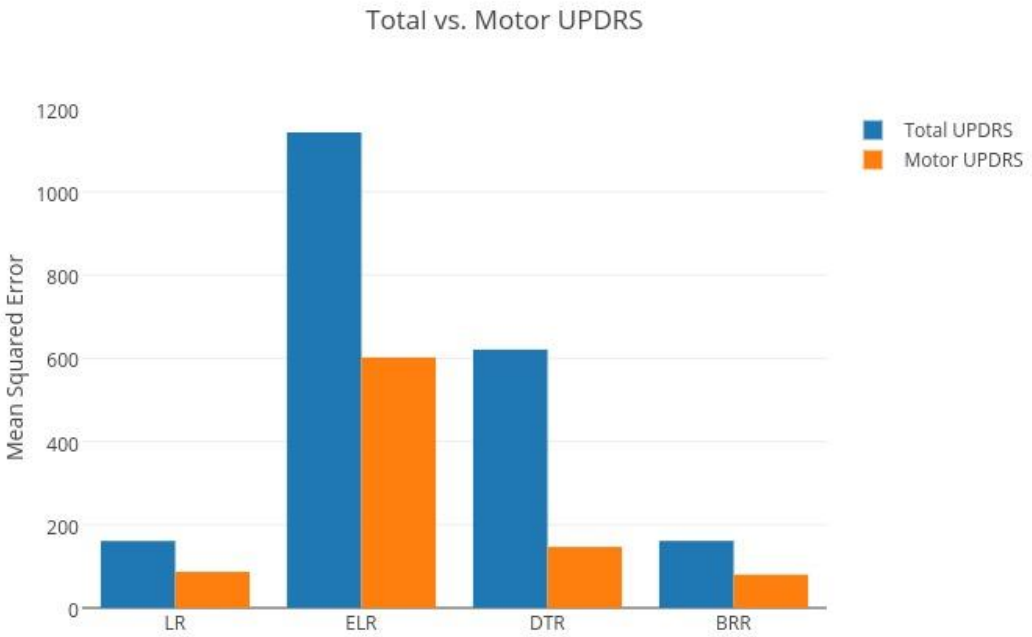
- Approximately 200 voice samples from 42 participants
- Training-Test Split 32/10
- 16 interesting features for each sample
- Our aim is to predict the unified Parkinson's disease rating scale (UPDRS) which is a standard rating scale used to follow the longitudinal course of Parkinson's disease.
- Total UPDRS and Motor UPDRS
    - Part I: evaluation of mentation, behavior, and mood
    - Part II: self-evaluation of the activities of daily life (ADLs) including speech, swallowing, handwriting, dressing, hygiene, falling, salivating, turning in bed, walking, and cutting food
    - Part III: clinician-scored monitored motor evaluation
    - Part IV: complications of therapy
    - Part V: Hoehn and Yahr staging of severity of Parkinson's disease
    - Part VI: Schwab and England ADL scale


Motor UPDRS
Total UPDRS
0.06
0.04
0.02
0
10
20
30
40
50

Jitter(%) Jitter(Abs) Jitter:RAP Jitter:PPQ5 Jitter:DDP	Several measures of variation in fundamental frequency
Shimmer Shimmer(dB) Shimmer:APQ3 Shimmer:APQ5 Shimmer:APQ11 Shimmer:DDA	Several measures of variation in amplitude
NHR HNR	Two measures of ratio of noise to tonal components in the voice
RPDE	A nonlinear dynamical complexity measure
DFA	Signal fractal scaling exponent
PPE	A nonlinear measure of fundamental frequency variation

MSE with off the shelf methods

- Linear Regression
  - Total UPDRS: 235.68
  - Motor UPDRS: 96.15
- Exponential Linear Regression
  - Total UPDRS: 1116.1
  - Motor UPDRS: 607.56
- Decision Tree Regression
  - Total UPDRS: 714.16
  - Motor UPDRS: 370.29
- Bayesian Ridge Regression
  - Total UPDRS: 174.4
  - Motor UPDRS: 97.76



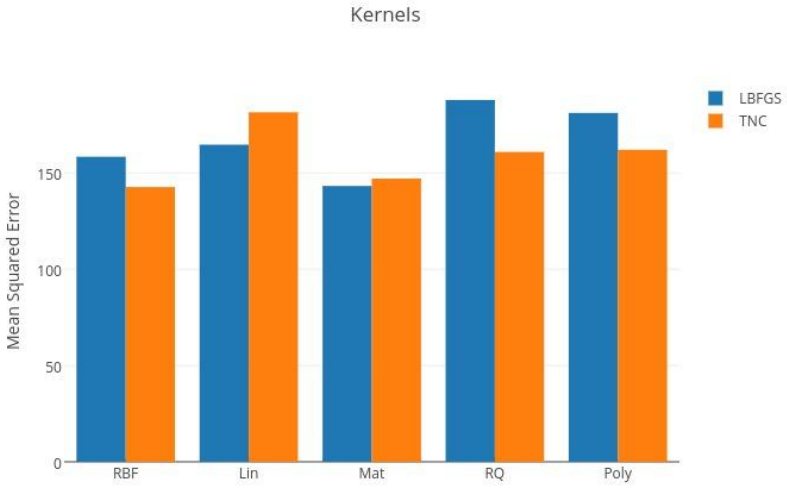
Can we do better?

- Gaussian Process Regression
  - Kernel Choice
    - RBF
    - Matern
    - Linear
    - Polynomial
    - Rational Quadratic
  - Hyperparameter Optimization
    - Scaled Conjugate Gradients
    - Tsybakov Noise Condition
    - Limited-memory BFGS
  - Dealing with large amounts of data. Sparse GPs?
- Gaussian Process Classification

GP Regression

- RBF kernel
  - Limited-memory BFGS: 158.45
  - **Tsybakov Noise Condition : 142.71**
- Linear Kernel
  - Limited-memory BFGS: 164.70
  - Tsybakov Noise Condition : 181.53
- Matern Kernel
  - **Limited-memory BFGS: 143.26**
  - Tsybakov Noise Condition:147.10
- Polynomial Kernel
  - Limited-memory BFGS: 181.20
  - Tsybakov Noise Condition: 162.05

- Rational Quadratic Kernel
  - Limited-memory BFGS: 187.90
  - Tsybakov Noise Condition : 160.95



Kernel Combinations

- RatQuad + Matern
  - 167.33
- RBF + Matern
  - 127.39
- Linear + Matern
  - 160.37
- Poly + Matern
  - 182.50
- RBF + Matern + RatQuad
  - 186.43
- Matern + (RBF*Linear)
  - 146.16
- Matern + (Linear*RatQuad)
  - 169.29
- Matern + (RBF*Poly)
  - 161.71
- Matern+RatQuad + (RBF*Linear)
  - **107.34**
- Matern + Linear + (RBF*RatQuad)
  - 204.08

Gaussian Regression Classification

- Use binary classification to predict whether or not the patient has PD
- Uses a Gaussian likelihood function
- If probability of PD is greater than 0.50 classify as positive
- Naive Bayes
  - 72% correct
- Kernels used
  - RBF : 66% correct
  - Matern : 62% correct
  - RatQuad : 68% correct
  - Others kernels did not work well

Conclusions and Future Work

- Choosing a kernel is hard!
- Best MSE = 107.34
- Gaussian Process Regression achieves better results than other forms of regression.
- Gaussian Classification ~70% at best.
- We still think we can do better
    - Bayesian Neural Networks
    - Bayesian SVM

References

Little MA, McSharry PE, Hunter EJ, Ramig LO (2009), 'Suitability of dysphonia measurements for telemonitoring of Parkinson's disease',IEEE Transactions on Biomedical Engineering, 56(4):1015-1022

Little MA, McSharry PE, Roberts SJ, Costello DAE, Moroz IM. 'Exploiting Nonlinear Recurrence and Fractal Scaling Properties for Voice Disorder Detection',BioMedical Engineering OnLine 2007, 6:23 (26 June 2007)

https://archive.ics.uci.edu/ml/datasets/Parkinsons+Telemonitoring