Automated Fish Classification

Using Unprocessed Fatty Acid Chromatographic Data

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PSO [1] inspired by social behaviour of animals

Topics

1. Catfishing
2. Fish Oil
3. Gas Chromatography
4. Classification
5. Intepretable
6. Feature Selection

Have you been catfished? [2]

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Popular restaurant accused of serving cheap Vietnamese catfish to customers who thought they were getting Australian dory

- **A Melbourne restaurant has been accused of serving catfish to customers**
- **Hunky Dory has allegedly been selling frozen fillets of basa as dory**
- **Owner Greg Robotis has denied allegations he is misleading customers**
- **The City of Port Phillip is investigating Hunky Dory's Port Melbourne store**

By HARRY PEARL FOR DAILY MAIL AUSTRALIA

PUBLISHED: 14:31 AEDT, 27 May 2016 | **UPDATED:** 16:08 AEDT, 27 May 2016

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A Melbourne restaurant has been accused of serving a Vietnamese catfish to customers who believe they are ordering Dory.

A whistleblower has alleged that Hunky Dory outlets have been selling frozen fillets of basa, a species of catfish native to the Mekong basin, as fish-of-the-day dory, **The Age** reports.

Owner Greg Robotis has denied the claims and said inexperienced staff may have been calling the fish the wrong name.

Aussies! No surprises there...

Catfishing [2], Mislabelling [3], and Quality Assurance [4]

Nutrition Facts

6 servings per container
Serving size 4-5 ounces(187g)

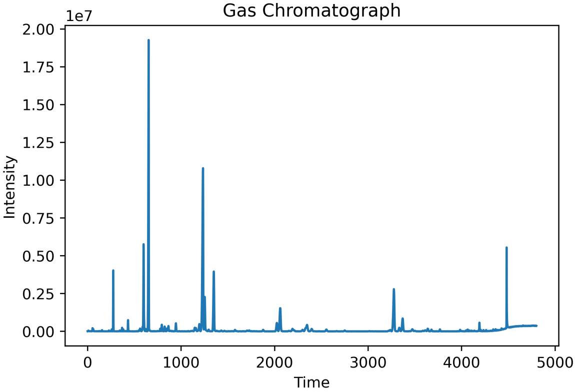
Amount per serving
Calories 200

	% Daily Value*
Total Fat 5g	**6%**
Saturated Fat 0.5g	**3%**
Trans Fat 0g	
Cholesterol 80mg	**27%**
Sodium 610mg	**27%**
Total Carbohydrate 10g	**4%**
Dietary Fiber 0g	**0%**
Total Sugars 3g	
Includes 0g Added Sugars	**0%**
Protein 27g	
Vitamin D 2mcg	10%
Calcium 79mg	6%
Iron 3mg	15%
Potassium 519mg	10%

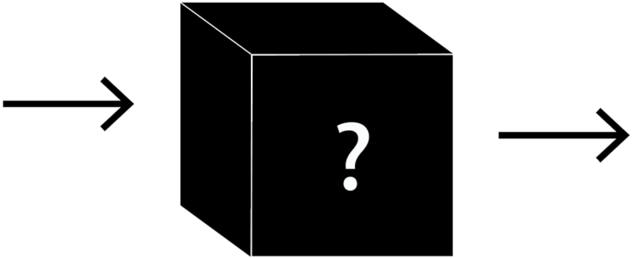
*The % Daily Value tells you how much a nutrient in a serving of food contributes to a daily diet. 2,000 calories a day is used for general nutrition advice.

Fish oil is brain food! [5, 6]

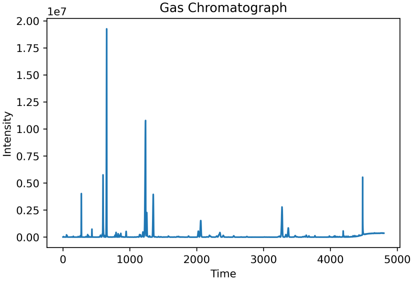
Fish oil analyzed with Gas Chromatography! [7]



Fish oil analysis can't be blackbox! [8, 9]

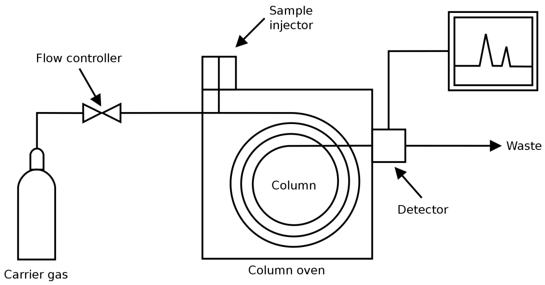


Gas Chromatography [4] ≈ Chemical Fingerprint



Gas Chromatography: Steps

1. Apply heat to liquid.
2. Evaporate into gas.
3. Travel through long tube.
4. Detector measures intensity.



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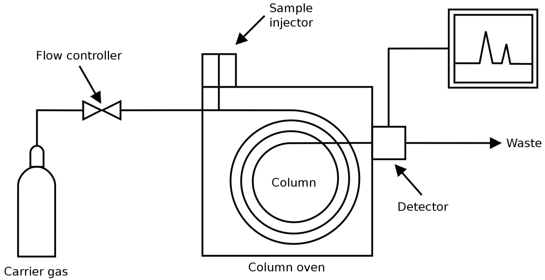

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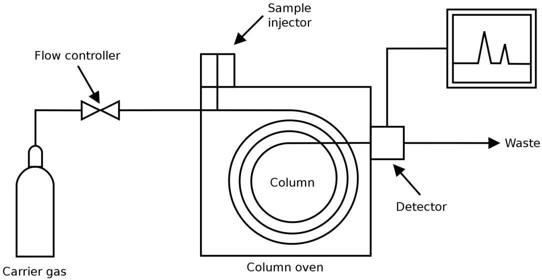

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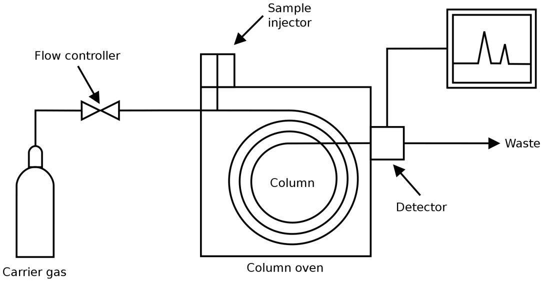

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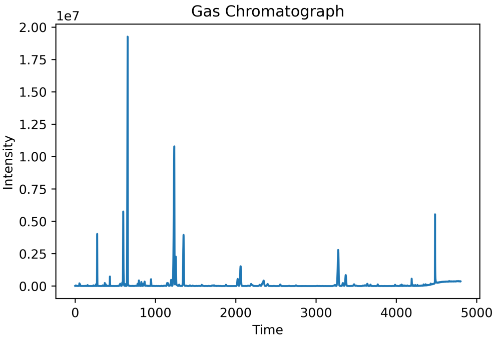

Classification: Datasets

Dataset
Species 
Parts 

Classification: Methods

Dataset	**Method**
	KNN [10]
	RF [11]
Species 	DT [12]
Parts 	NB [13]
	SVM [14]

Classification: Balanced Accuracy, Cross-validation

Dataset	Method	**Train**	**Test**
	KNN [10]	83.57	74.88
	RF [11]	100.0	85.65
Species 	DT [12]	100.0	76.98
	NB [13]	79.54	75.27
	SVM [14]	100.0	98.33
	KNN	68.95	43.61
	RF	100.00	72.60
Parts 	DT	100.00	60.14
	NB	65.54	48.61
	SVM	100.00	79.86

Classification: Results

Dataset	Method	Train	Test
Species 	KNN [10]	83.57	74.88
	RF [11]	100.0	85.65
	DT [12]	100.0	76.98
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Classification: SVM near-perfect on fish species

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Classification: Body parts harder than fish species

Dataset	Method	Train	Test
	KNN [10]	83.57	74.88
	RF [11]	100.0	85.65
Species 	DT [12]	100.0	76.98
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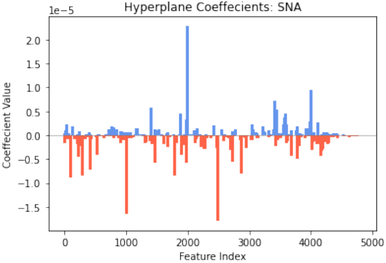
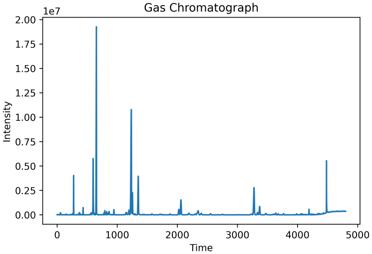
Classification: Avoid Catfishing [2] & Mislabelling [3]

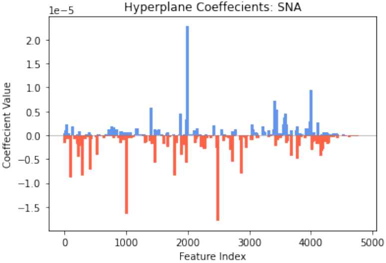
Intepretable Model - A Hyperplane



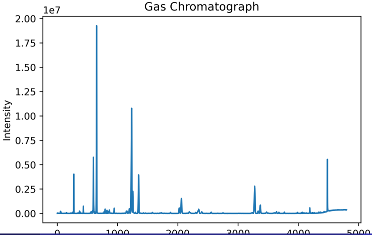
Interpretable Instance - A Chromatograph



Intepretable Comparison - Hyperplane vs. Chromatograph



post hoc analysis to build trust in the prediction 



Feature Selection: Dataset

Dataset

Species 

Parts 

Feature Selection: Methods

Dataset	**Method**
	ReliefF [15]
Species 	mRMR [16]
	χ^2 [17]
Parts 	PSO [1]
	Full

Feature Selection: # Features given for Best Run

Dataset	Method	**# Features**
Species 	ReliefF [15]	359
	mRMR [16]	1500
	χ^2 [17]	3250
	PSO [1]	1192
	Full	4800
Parts 	ReliefF	1650
	mRMR	1500
	χ^2	1550
	PSO	1223
	Full	4800

Feature Selection: Balanced Accuracy, Cross-validation

Dataset	Method	# Features	**Train**	**Test**
	ReliefF [15]	359	100.0	98.33
	mRMR [16]	1500	100.0	99.17
Species 	χ^2 [17]	3250	100.0	98.33
	PSO [1]	1192	100.0	99.17
	Full	4800	100.0	98.33
	ReliefF	1650	100.0	84.44
	mRMR	1500	100.0	86.94
Parts 	χ^2	1550	100.0	82.50
	PSO	1223	100.0	84.31
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Feature Selection: Results

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Feature Selection: PSO & MRMR improve accuracy!

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Feature Selection: PSO uses 1/4 features, x4 faster!

Dataset	Method	# **Features**	Train	Test
	ReliefF [15]	359	100.0	98.33
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Parts 	χ^2	1550	100.0	82.50
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Feature Selection: MRMR best for body parts!

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	ReliefF [15]	359	100.0	98.33
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Parts 	χ^2	1550	100.0	82.50
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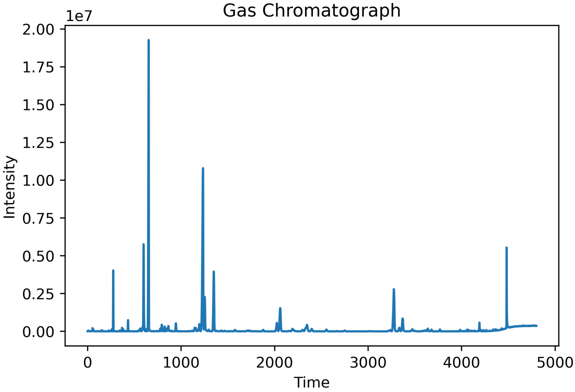
Feature Selection: Reduce GC time [4], simpler models [18]



TLDR;

Linear SVM can accurately predict fish species, **PSO** makes that process 4 times faster, producing an **accurate**, **interpretable** and **efficient** model for **Gas Chromatography**.

Download the slides, paper, poster.

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