

# Automated Fish Classification

## Using Unprocessed Fatty Acid Chromatographic Data

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# Island Bay, Wellington, New Zealand



# 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



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]

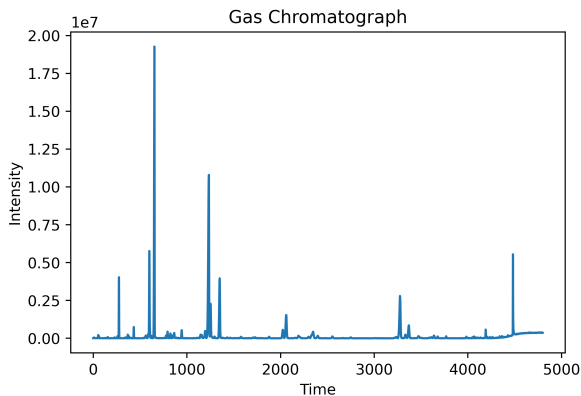
Nutrition Facts	
6 servings per container	
<b>Serving size</b>	<b>4-5 ounces(187g)</b>
Amount per serving	
<b>Calories</b>	<b>200</b>
% Daily Value*	
Total Fat 5g	6%
Saturated Fat 0.5g	3%
Trans Fat 0g	
Cholesterol 80mg	27%
Sodium 610mg	27%
Total Carbohydrate 10g	4%
Dietary Fiber 0g	0%
Total Sugars 3g	
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]

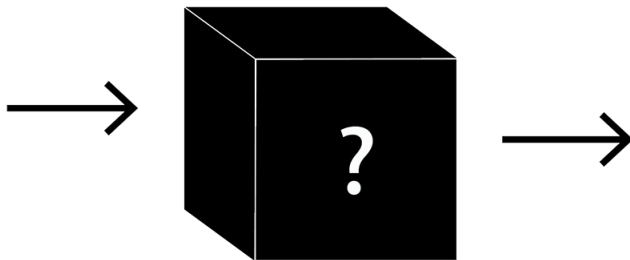


# Fish oil analyzed with Gas Chromatography! [7]

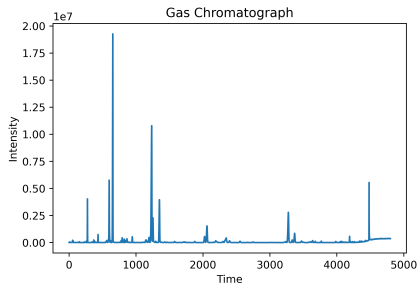




# Fish oil analysis can't be blackbox! [8, 9]

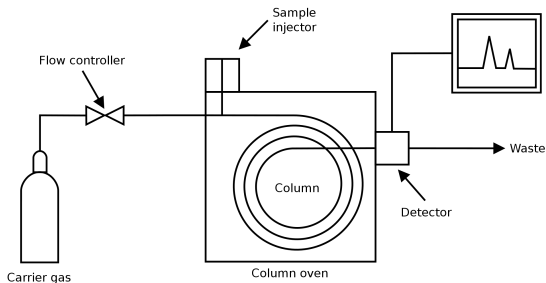


# Gas Chromatography [4] $\approx$ Chemical Fingerprint



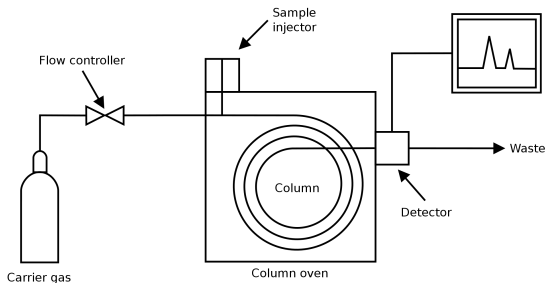
# Gas Chromatography: Steps

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



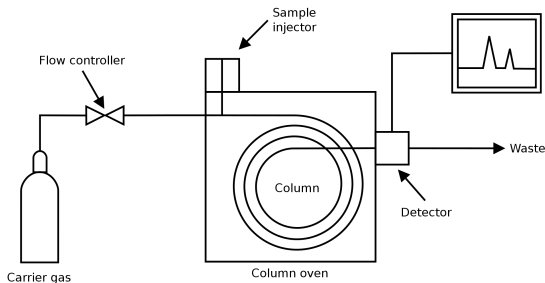
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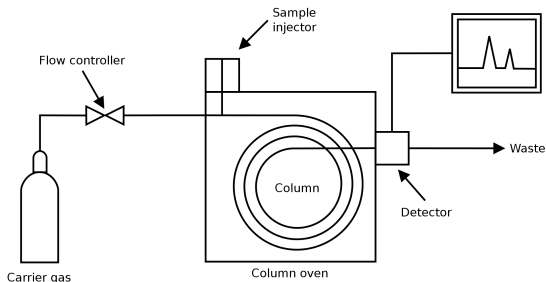
# Gas Chromatography: Steps

- 1 Apply heat to liquid.
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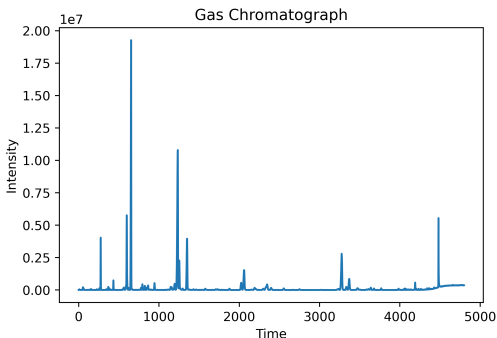
# Gas Chromatography: Steps

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



# Gas Chromatography: Steps

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



# Classification: Datasets

## Dataset



Species 

Parts 







# Classification: Methods

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





# Classification: Balanced Accuracy, Cross-validation

Dataset	Method	Train	Test
Species 	KNN [10]	83.57	74.88
	RF [11]	100.0	85.65
	DT [12]	100.0	76.98
	NB [13]	79.54	75.27
	SVM [14]	100.0	98.33
Parts 	KNN	68.95	43.61
	RF	100.00	72.60
	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
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# Classification: SVM near-perfect on fish species

Dataset	Method	Train	Test
Species 	KNN [10]	83.57	74.88
	RF [11]	100.0	85.65
	DT [12]	100.0	76.98
	NB [13]	79.54	75.27
	<b>SVM [14]</b>	<b>100.0</b>	<b>98.33</b>
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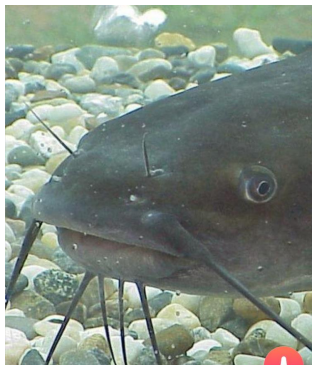


# Classification: Body parts harder than fish species

Dataset	Method	Train	Test
Species 	KNN [10]	83.57	74.88
	RF [11]	100.0	85.65
	DT [12]	100.0	76.98
	NB [13]	79.54	75.27
	<b>SVM [14]</b>	<b>100.0</b>	<b>98.33</b>
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	DT	100.00	60.14
	NB	65.54	48.61
	<b>SVM</b>	<b>100.00</b>	<b>79.86</b>



# Classification: Avoid Catfishing [2] & Mislabelling [3]



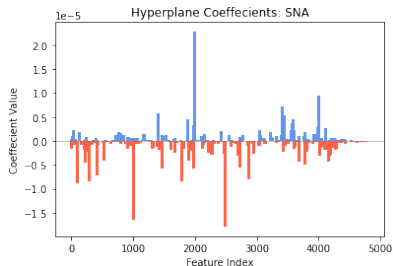
**Real Human, 19**

📍 8 kilometres away

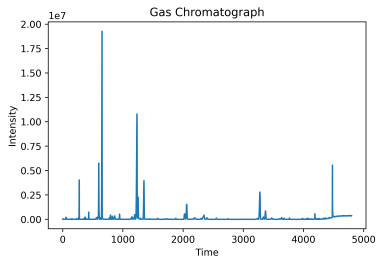
Hello i am real human i enjoy the human hobbies of breathing and walking around on my leg



# Interpretable Model - A Hyperplane

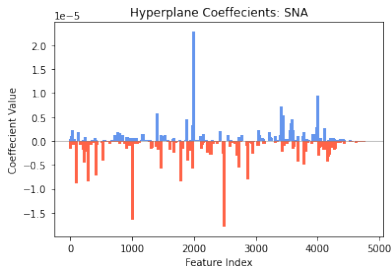


# Interpretable Instance - A Chromatograph

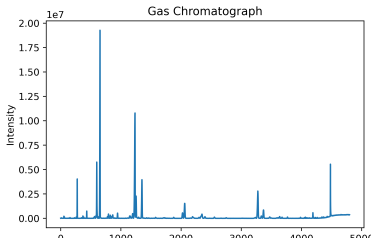




# Intepretable Comparison - Hyperplane vs. Chromatograph



post hoc analysis to build trust in the prediction



# Feature Selection: Dataset



## Dataset

Species 

Parts 





# Feature Selection: Methods

Dataset	Method
Species 	ReliefF [15] mRMR [16]
Parts 	$\chi^2$ [17] PSO [1] Full





# Feature Selection: # Features given for Best Run

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





# Feature Selection: Balanced Accuracy, Cross-validation

Dataset	Method	# Features	Train	Test
Species 	ReliefF [15]	359	100.0	98.33
	mRMR [16]	1500	100.0	99.17
	$\chi^2$ [17]	3250	100.0	98.33
	PSO [1]	1192	100.0	99.17
	Full	4800	100.0	98.33
Parts 	ReliefF	1650	100.0	84.44
	mRMR	1500	100.0	86.94
	$\chi^2$	1550	100.0	82.50
	PSO	1223	100.0	84.31
	Full	4800	100.0	79.86





# Feature Selection: Results

Dataset	Method	# Features	Train	Test
Species 	ReliefF [15]	359	100.0	98.33
	mRMR [16]	1500	100.0	99.17
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	PSO	1223	100.0	84.31
	Full	4800	100.0	79.86





# Feature Selection: PSO & MRMR improve accuracy!

Dataset	Method	# Features	Train	Test
Species 	ReliefF [15]	359	100.0	98.33
	<b>mRMR [16]</b>	<b>1500</b>	<b>100.0</b>	<b>99.17</b>
	$\chi^2$ [17]	3250	100.0	98.33
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	$\chi^2$	1550	100.0	82.50
	PSO	1223	100.0	84.31
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# Feature Selection: PSO uses 1/4 features, x4 faster!

Dataset	Method	# Features	Train	Test
Species 	ReliefF [15]	359	100.0	98.33
	<b>mRMR [16]</b>	<b>1500</b>	<b>100.0</b>	<b>99.17</b>
	$\chi^2$ [17]	3250	100.0	98.33
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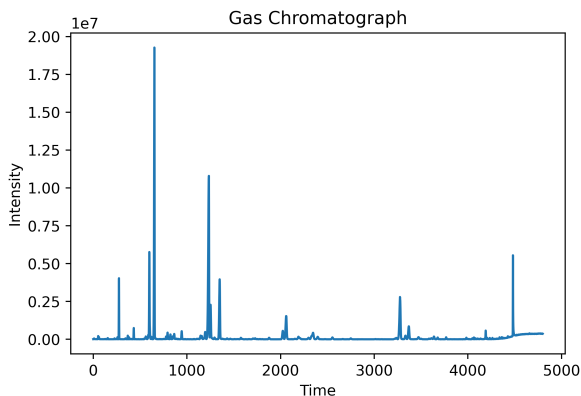


# Feature Selection: MRMR best for body parts!

Dataset	Method	# Features	Train	Test
Species 	ReliefF [15]	359	100.0	98.33
	<b>mRMR [16]</b>	<b>1500</b>	<b>100.0</b>	<b>99.17</b>
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# Feature Selection: Reduce GC time [4], simpler models [18]



**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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