Automated Fish Classification

Using Unprocessed Fatty Acid Chromatographic Data

Jesse Wood[1] Bach Hoai Nguyen[1] Bing Xue[1] Mengjie Zhang[1] Daniel Killeen[2]

[1]School of Engineering and Computer Science — Te Kura Mātai Pūkaha, Pūrorohiko
Victoria University of Wellington — Te Herenga Waka
[2]New Zealand Institute for Plant and Food Research Limited, Nelson, New Zealand

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]

Daily Mail AUSTRALIA

Home | U.K. | U.S. | News | World News | Sport | TV&Showbiz | Femail AU | Health | Scien

Monkeypox | Covid-19 | Russia-Ukraine War | Breaking News | Sydney | Melbourne | Brisbane | New Zealand |

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

Share 47 shares 9 View comments

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)

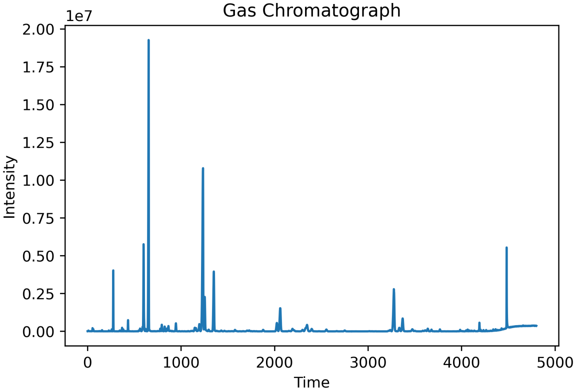
Amount per serving
Calories 200

	% 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%

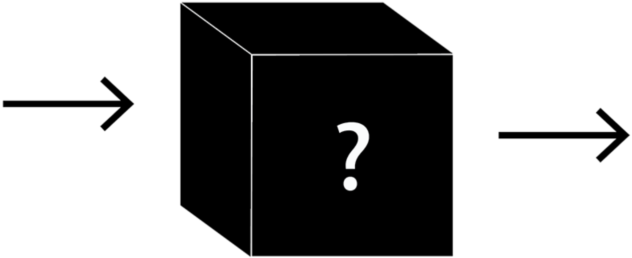
*The % Daily Value tells you how much a nutrient in a serving of food contributes to a daily diet. 2,000 calories a day is used for general nutrition advice.

Fish oil is brain food! [5, 6]

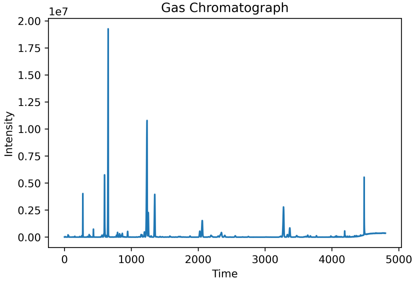
Fish oil analyzed with Gas Chromatography! [7]



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

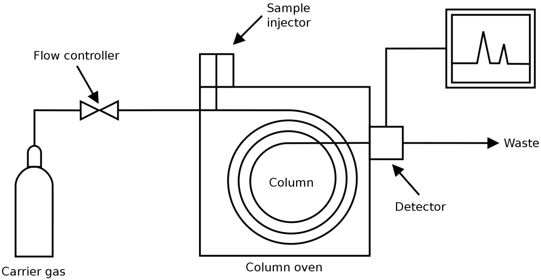


Gas Chromatrography [4] ≈ Chemical Fingerprint



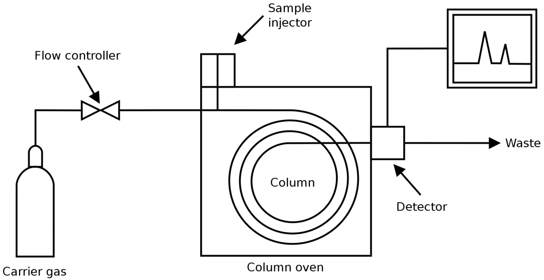
Gas Chromatrography: Steps

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



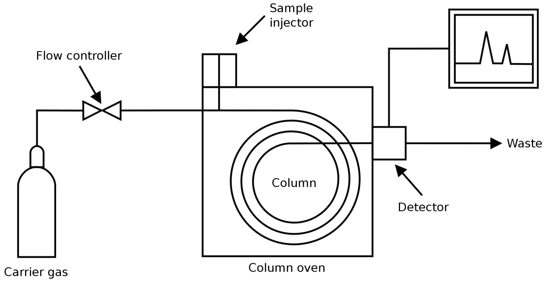
Gas Chromatrography: Steps

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



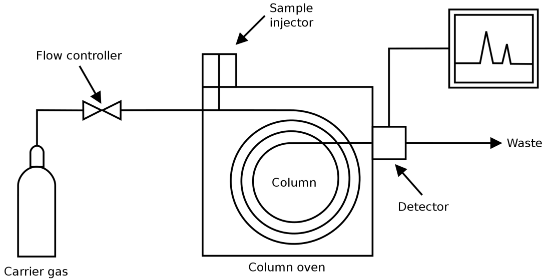
Gas Chromatrography: Steps

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



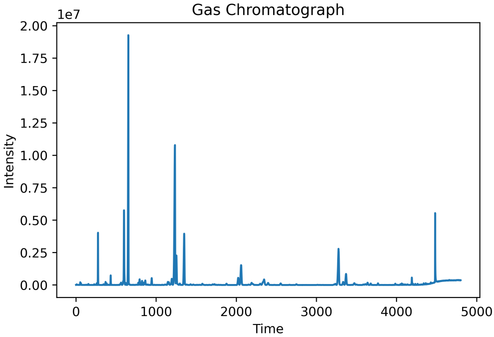
Gas Chromatrography: Steps

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



Gas Chromatrography: 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**
	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
	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: SVM near-perfect on fish species

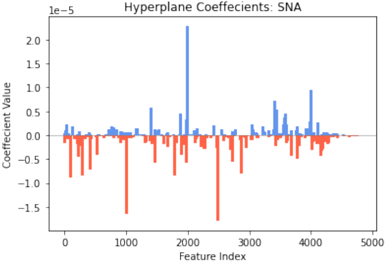
Dataset	Method	Train	Test
Species 	KNN [10]	83.57	74.88
	RF [11]	100.0	85.65
	DT [12]	100.0	76.98
	NB [13]	79.54	75.27
	SVM [14]	**100.0**	**98.33**
Parts 	KNN	68.95	43.61
	RF	100.00	72.60
	DT	100.00	60.14
	NB	65.54	48.61
	SVM	100.00	79.86

Classification: Body parts harder than fish species

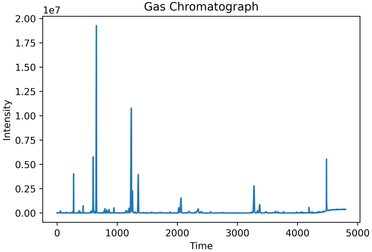
Dataset	Method	Train	Test
	KNN [10]	83.57	74.88
	RF [11]	100.0	85.65
Species 	DT [12]	100.0	76.98
	NB [13]	79.54	75.27
	SVM [14]	**100.0**	**98.33**
	KNN	68.95	43.61
	RF	100.00	72.60
Parts 	DT	100.00	60.14
	NB	65.54	48.61
	SVM	**100.00**	**79.86**

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

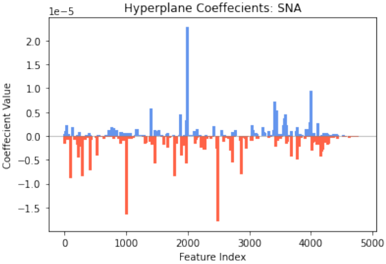
Intepretable Model - A Hyperplane



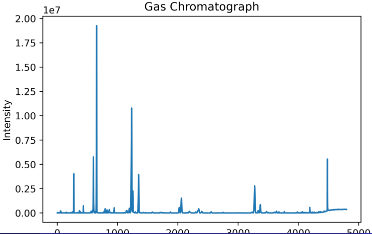
Interpretable Instance - A Chromatograph



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**
Species 	ReliefF [15]
Parts 	mRMR [16]
	χ^2 [17]
	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**
Species 	ReliefF [15]	359	100.0	98.33
	mRMR [16]	1500	100.0	99.17
	χ^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
	χ^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
	χ^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
	χ^2	1550	100.0	82.50
	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
	mRMR [16]	**1500**	**100.0**	**99.17**
	χ^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**
	χ^2	1550	100.0	82.50
	PSO	1223	100.0	84.31
	Full	4800	100.0	79.86

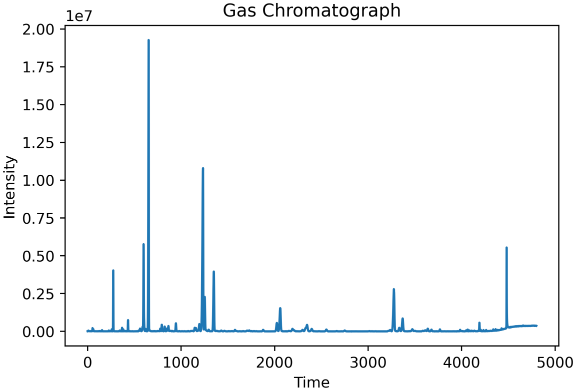
Feature Selection: PSO uses 1/4 features, x4 faster!

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
	Full	4800	100.0	79.86

Feature Selection: MRMR best for body parts!

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
	Full	4800	100.0	79.86

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.

[1] J. Kennedy and R. C. Eberhart, "Particle swarm optimization," in *Proceedings of ICNN'95-international conference on neural networks*, vol. 4. IEEE, 1995, pp. 1942–1948.

[2] H. P. F. D. M. Australia, "Melbourne restaurant hunky dory accused of serving catfish to customers instead of dory," May 2016. [Online]. Available: https://www.dailymail.co.uk/news/article-3611999/Melbourne-restaurant-Hunky-Dory-accused-serving-catfish-customers-ins html

[3] M. Á. Pardo, E. Jiménez, and B. Pérez-Villarreal, "Misdescription incidents in seafood sector," *Food Control*, vol. 62, pp. 277–283, 2016.

[4] K. Eder, "Gas chromatographic analysis of fatty acid methyl esters," *Journal of Chromatography B: Biomedical Sciences and Applications*, vol. 671, no. 1-2, pp. 113–131, 1995.

[5] A. P. Simopoulos, "Evolutionary aspects of diet: the omega-6/omega-3 ratio and the brain," *Molecular neurobiology*, vol. 44, no. 2, pp. 203–215, 2011.

[6] M. L. Panse and S. D. Phalke, "World market of omega-3 fatty acids," *Omega-3 Fatty Acids*, pp. 79–88, 2016.

[7] C. Black, O. P. Chevallier, K. M. Cooper, S. A. Haughey, J. Balog, Z. Takats, C. T. Elliott, and C. Cavin, "Rapid detection and specific identification of offals within minced beef samples utilising ambient mass spectrometry," *Scientific reports*, vol. 9, no. 1, pp. 1–9, 2019.

[8] K. Bi, D. Zhang, T. Qiu, and Y. Huang, "Gc-ms fingerprints profiling using machine learning models for food flavor prediction," *Processes*, vol. 8, no. 1, p. 23, 2020.

[9] D. D. Matyushin and A. K. Buryak, "Gas chromatographic retention index prediction using multimodal machine learning," *Ieee Access*, vol. 8, pp. 223 140–223 155, 2020.

[10] E. Fix and J. L. Hodges, "Discriminatory analysis. nonparametric discrimination: Consistency properties," *International Statistical Review/Revue Internationale de Statistique*, vol. 57, no. 3, pp. 238–247, 1989.

[11] T. K. Ho, "Random decision forests," in *Proceedings of 3rd international conference on document analysis and recognition*, vol. 1. IEEE, 1995, pp. 278–282.

[12] W.-Y. Loh, "Classification and regression trees," *Wiley interdisciplinary reviews: data mining and knowledge discovery*, vol. 1, no. 1, pp. 14–23, 2011.

[13] D. J. Hand and K. Yu, "Idiot's bayes—not so stupid after all?" *International statistical review*, vol. 69, no. 3, pp. 385–398, 2001.

[14] C. Cortes and V. Vapnik, "Support-vector networks," *Machine learning*, vol. 20, no. 3, pp. 273–297, 1995.

[15] M. Robnik-Šikonja and I. Kononenko, "Theoretical and empirical analysis of relieff and rrelieff," *Machine learning*, vol. 53, no. 1, pp. 23–69, 2003.

[16] C. Ding and H. Peng, "Minimum redundancy feature selection from microarray gene expression data," *Journal of bioinformatics and computational biology*, vol. 3, no. 02, pp. 185–205, 2005.

[17] H. Liu and R. Setiono, "Chi2: Feature selection and discretization of numeric attributes," in *Proceedings of 7th IEEE International Conference on Tools with Artificial Intelligence*. IEEE, 1995, pp. 388–391.

[18] Z. Zhao, R. Anand, and M. Wang, "Maximum relevance and minimum redundancy feature selection methods for a marketing machine learning platform," in *2019 IEEE international conference on data science and advanced analytics (DSAA)*. IEEE, 2019, pp. 442–452.