



## Bayesian Network Classification of Gastrointestinal Bleeding

Nazziwa Aisha<sup>1\*</sup>, Mohd Bakri Adam<sup>2</sup>, Shamarina Shohaimi<sup>1</sup> and Aida Mustapha<sup>3</sup>

<sup>1</sup>Department of Mathematics, Faculty of Science, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia

<sup>2</sup>Department of Biology, Faculty of Science, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia

<sup>3</sup>Department of Computer Science, Faculty of Science, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia

### ABSTRACT

The source of gastrointestinal bleeding (GIB) remains uncertain in patients presenting without hematemesis. This paper aims at studying the accuracy, specificity and sensitivity of the Naive Bayesian Classifier (NBC) in identifying the source of GIB in the absence of hematemesis. Data of 325 patients admitted via the emergency department (ED) for GIB without hematemesis and who underwent confirmatory testing were analysed. Six attributes related to demography and their presenting signs were chosen. NBC was used to calculate the conditional probability of an individual being assigned to Upper Gastrointestinal bleeding (UGIB) or Lower Gastrointestinal bleeding (LGIB). High classification accuracy (87.3 %), specificity (0.85) and sensitivity (0.88) were achieved. NBC is a useful tool to support the identification of the source of gastrointestinal bleeding in patients without hematemesis.

*Keywords:* Bayesian network classifiers, Emergency department, hematemesis, upper gastrointestinal bleeding, Naive Bayes classifier, lower gastrointestinal bleeding, data mining

#### Article history:

Received: 31 December 2012

Accepted: 27 May 2013

#### Email addresses:

Nazziwa Aisha (aishanazziwa@yahoo.ca),

Mohd Bakri Adam (bakri@upm.edu.my),

Shamarina Shohaimi (sshohaimi@yahoo.com),

Aida Mustapha (aida\_m@upm.edu.my)

\*Corresponding Author

### INTRODUCTION

Acute gastrointestinal bleeding (GIB) is considered a potentially life threatening condition that requires prompt assessment and aggressive medical management. Older patients, especially those over age 50 years, make up a rising proportion of patients with GIB, and mortality rates in this group have remained relatively high (Vreeburg *et al.*, 1997; Crooks *et al.*, 2011). Further reductions in mortality will require the introduction of

novel methods to help with identification of the cohort requiring aggressive resuscitation and endoscopic intervention to prevent complications and death from ongoing bleeding (Dhahab & Barkun, 2012). Delays in intervention often result from failure to adequately recognise the source and severity of the bleeding. GIB is described by the anatomical area that is bleeding and is classified as either upper gastrointestinal bleeding (UGIB) or lower gastrointestinal bleeding (LGIB). The anatomic landmark is the ligament of Treitz which extends from the small intestine at the duodenojejunal junction. When the bleeding is proximal to the ligament, it is classified as UGIB and if it is distal to the ligament, it is classified as LGIB.

In the emergency department (ED), when patients show signs of hematemesis i.e. vomiting of blood, (Society and Committee, 2002), it is clear that the source of bleeding is from the upper gastrointestinal tract. However, when there is no hematemesis the source of bleeding is unclear. The source of bleed determines management of the bleeding. It will determine the type of physician to be assigned and the timing (Barkun *et al.*, 2010). The primary diagnostic tool of choice in patients with acute upper gastrointestinal bleeding is esophagogastroduodenoscopy (EGD) (Kovacs *et al.*, 2002; Manning-Dimmitt *et al.*, 2005) and for lower gastrointestinal bleeding it is colonoscopy (Jensen *et al.*, 1997). These tools aid diagnosis, allow treatments that can stop bleeding to be delivered and yield information that help in prediction of outcomes (Albeldawi *et al.*, 2010).

Although diagnosis of GIB is best done by a gastroenterologist, it is not always feasible because of resource, time and cost constraints (Gralnek & Dulai, 2004; Quirk *et al.*, 1997). Without the gastroenterologist, physicians are left to determine the source of bleeding using symptoms and demographic data only. Of late, the use of nasogastric aspiration (NGA) has been advocated to localise bleeding (Witting *et al.*, 2004; Anderson & Witting, 2010) but it is a painful procedure and it does not work well for patients without hematemesis. The predictors identified in clinical and epidemiological studies to predict UGIB in patients without hematemesis are that patients are aged below 50; the colour of the material passed through the rectum is black and the ratio of blood urea nitrogen to creatinine is 30 and above (Witting *et al.*, 2006), while the factors for LGIB are hemodynamic instability (SBP=90mmHg, Heart rate > 100/min), a Hemoglobin level of 6g/dl and initial hematocrit of 35 % (Velayos *et al.*, 2004; Parkes *et al.*, 1993). Medications, especially those of NSAID, increase the risk of GIB, leading to hospital admission (Lanas *et al.*, 2006). The incidence of LGIB is higher in men than in women, and patients with prior episodes of UGIB are more likely to bleed from the same lesion. Tarone *et al.* (2004) state that 60 % of patients with a history of UGIB bleed from the same lesion.

To assist the emergency department physician in diagnosing the patients more efficiently and effectively, mathematical models must be developed to identify the source of GIB. Classification models have the ability to identify the source of GIB, which is needed for intervention and to allow optimisation of care and healthcare resource allocation amongst patients with acute GIB (Chu *et al.*, 2008). In this study, we use a naive Bayesian classifier (NBC) to predict the source of GIB. The graphical nature of NBC makes it easy for physicians to understand and use (Mittal and Kassim, 2007; Jensen, 1996). The NBC can be used to predict the source of bleeding using clinical and laboratory information available within a few hours of patient presentation.

## BAYESIAN NETWORK CLASSIFIERS

Classification is a basic task in data analysis that constructs a function from labelled training data. The training data has both input and output objects. A supervised learning algorithm is used to construct a function called a classifier. When output is discrete we call it a classification algorithm and if continuous, a regression function. Bayesian network classifiers (BNC) are a group of generative classifiers that have performed well in many classification tasks. The NBC is a BNC that has a predictive performance which is competitive with state-of-the-art classifiers like C4.5 (Quinlan, 1993). This classifier has previously been used in other medical studies (Kazmierska & Malicki, 2008; Wei *et al.*, 2011; Al-Aidaros *et al.*, 2012). The NB assumes conditional independence among the variables or attributes and learns conditional probabilities of each attribute,  $A_i$  given the class label,  $C$ . NBC predicts a new data point as the class with the highest posterior probability during classification by applying the Bayesian rule to compute the probability of  $C_i (1 \leq i \leq k)$  given the particular attributes, as shown in the equation  $\arg \max_{C_i} P(C_i) \prod_{j=1}^n P(A_j/C_i)$ .

When performing a classification, the NB partitions the data sets according to their class label into sub datasets. Then for each sub data set labelled  $C_i$  a maximum likelihood (ML) estimator  $P(A_j = a_{jk} | C_i)$  can be given by  $\frac{n_k + mp}{n + m}$  where  $n$  = the number of training examples for which  $C = C_i$ ,  $n_k$  = number of examples for which  $C = C_i$  and  $A = A_j$ ,  $p$  = a priori estimate for  $P(A_j = a_{jk} | C_i)$  and  $m$  = the equivalent sample size.

## METHODS

Data were collected from a retrospective cohort study of patients admitted through the ED for GI tract bleeding from unknown sources and followed until hospital discharge. This study has been described in detail previously (Witting *et al.*, 2006). The study used logistic regression analysis to identify clinical variables that independently predict an UGIB source. A total of 325 patients were admitted through the emergency department for GIB and were followed until hospital discharge. Eligible patients were 17 years or older, had heavy bleeding, as indicated by bloody or hemocult positive black stools, or hemocult positive dark stools if NGA was performed in the ED, were admitted in hospital through the ED for a principal diagnosis of GI tract bleeding and had confirmatory diagnostic testing within 3 days after admission. The exclusion criteria were: hematemesis, ostomy, an obvious anorectal source, such as hemorrhoids and admission for GI tract bleeding within the previous month. The institutional review board at each participating hospital approved the protocol.

### *Assessment*

The following information was recorded: sex, age, history of UGIB or LGIB, history of upper or lower GI cancer (yes/no), alcohol use (yes/no), tobacco use (yes/no), epigastric pain or tenderness, use of medication [prophylactic aspirin, non-steroidal anti-inflammatory drugs (NSAIDs), cirrhosis, steroids, warfarin iron, or bismuth] within the previous 2 weeks, colour of

blood in stools (black vs red), stool consistency (clots, tarry, diarrhea and not specified), initial resting and orthostatic vital signs and signs of cirrhosis. The colour and consistency of stools were based on the physician or patient's description. The diagnosed source of bleeding in a patient was obtained from the hospital discharge summary based on confirmatory testing such as EGD, colonoscopy, nuclear medicine scan, arteriography or surgery. In patients with unspecified gastrointestinal tract hemorrhage, classification was made based on a gastroenterologist's statement as to whether a finding indicated the site of hemorrhage.

Continuous variables were discretised e.g. age [50 and above (AboveEq50), below 50], Blood Urea Nitrogen to creatine ratio (BUN/CR) into [BUN/CR above or equal to 30 (AboveEq30), BUN/CR below 30 (below30)], Hematocrit into [above or equal to 30 (AboveEq30) and below 30 (below30)]. The discrete variables were consistence of stools (N=Not specified, T=Tarry, C=Clots, D=diarrhea), History of GIB (None, Lower=LGIB, Upper=UGIB) and colour of stools (red, black).

### *Methodology*

Predictors of GIB as seen in the literature were collected from the data. The model was trained to predict the source of bleeding and a 10-fold cross validation was carried out to assess the accuracy of the classifier (Kohavi, 1995). In the 10-fold cross-validation, the original data were randomly partitioned into 10 sub-samples. Of the 10 sub-samples, a single sub-sample was retained as the validation data for testing the model, and the remaining 9 sub-samples were used as training data. The cross validation process is then repeated 10 times, with each of the 10 sub-samples used only once as the validation data. The results from the 10-fold cross validation were then averaged to produce a single estimation.

During training, all information in the training set including the source of bleeding was provided to the NBC. In the testing phase, each patient datum, apart from source of bleeding, was entered into the trained NBC to infer the probability of the disease. The predicted source of bleeding probability and the known source of bleeding were then analysed using prediction accuracy and area under ROC curve (Hanley *et al.*, 1982). To evaluate the classifier, a standard approach to estimating the accuracy of NB was the prediction accuracy. Sensitivity analysis was done to identify the factors that influenced the source of bleeding. All calculations in this study were made with Naive Bayesian Classifier implemented in WEKA environment (Hall *et al.*, 2009). WEKA is a collection of machine learning algorithms for solving real-world data mining problems. It is written in Java and runs on almost any platform and enables testing databases applying different artificial intelligence systems.

### **RESULT**

A high classification accuracy of 87.3 % was achieved i.e. the results showed that out of a total of 325 cases, 284 patients had been accurately classified and 41 wrongly classified. Sensitivity of the system was 0.88 and specificity, 0.85. Fig.1 shows the initial probabilities in the naive Bayesian model used for predicting the source of GIB and their states e.g. the probability of

LGIB is 60.9 % and UGIB is 39.1 %. The probability of LGIB was higher than UGIB because in patients who show no signs of hematemesis, the most likely source of bleeding is LGIB. Since the factors in a naive Bayesian model are independent of each other, we can always include a number of factors even without feature selection. We included consistence and hematocrit to investigate the probabilities of the sources of bleeding, when only these factors were known. In general terms, the results indicate that source of bleeding is sensitive to a number of variables. The results of the sensitivity analysis showed two relatively high levels of mutual information for two variables: colour of stools at 33.2 % and history of gastrointestinal bleeding (HGIB) at 13.7 %, as shown by sensitivity analysis results captured in Table 1. Other factors are BUN/CR and hematocrit. The sensitivity analysis identified which data had a significant impact on the result, such that concentration could be given to finding accurate data for those items. The degree of sensitivity of one node (variable) to the class variable (source of bleeding) was shown by the mutual information (i.e. entropy reduction) while for continuous nodes it was shown by the variance reduction. All our variables were discretised; hence, we used the mutual information. The higher the mutual information, the greater the degree of sensitivity.

*Application of the Model*

With the naive Bayesian model, one is able to answer questions such as, “What is the probability of source of GIB given that age of a patient is below 50 years?” We can also predict the source of bleeding given any known symptoms. Because of maximum *a posteriori* (MAP) estimate in the NBC, the source with a higher posterior probability is the predicted source. If the information we know about the patient is that he passes black stools, the probability that he has UGIB rises to 76 % from the initial 39 % while the probability for LGIB falls to 23 %, and if he passes red stools, the probability is 87 % from the initial 60.9 %. This means that black stools is indicative of UGIB and red stools of LGIB. Figure 2 shows the posterior probability given only one piece of evidence that the patient has BUN/CR that is greater or equal to 30.

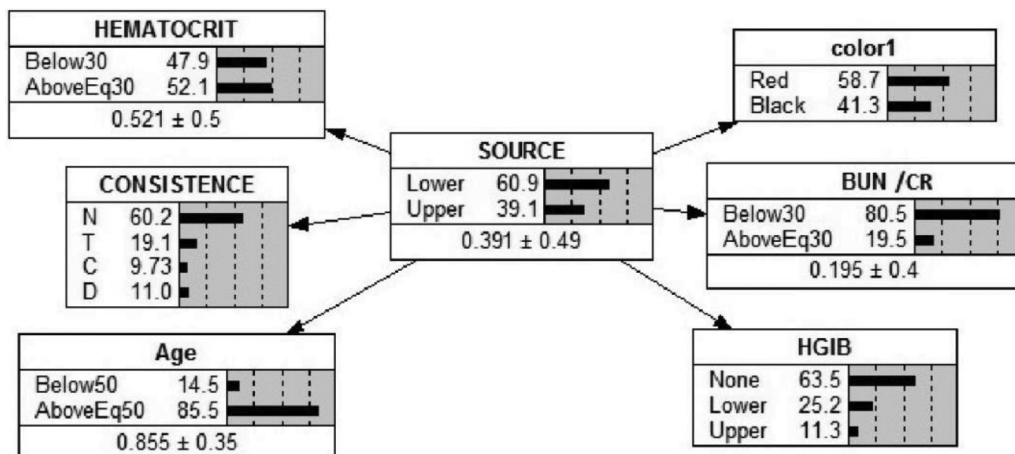
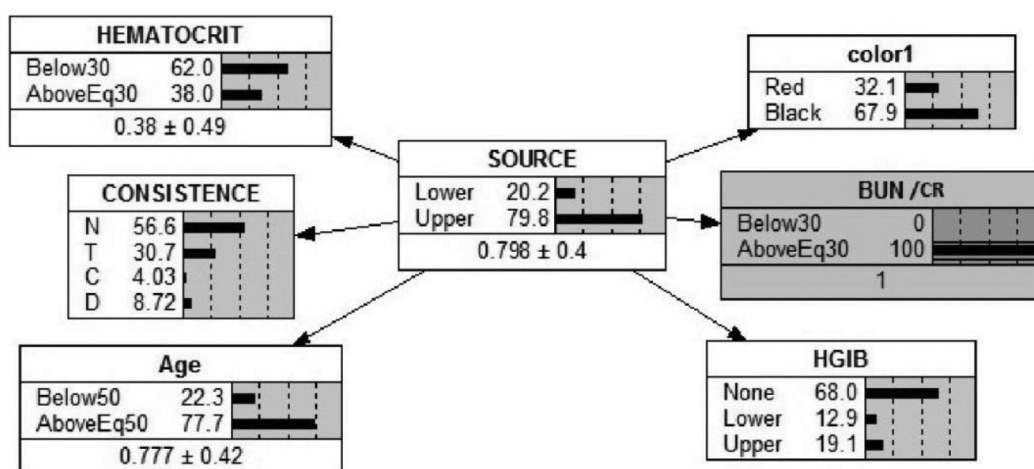


Fig.1: Naive Bayesian Classifier of Gastrointestinal Bleeding with Initial Probabilities

TABLE 1  
Sensitivity of Source of Gastrointestinal Bleeding to Findings at Other Nodes

| Node        | Variance Reduction | Percent | Mutual Info | Percent | Variance of Beliefs |
|-------------|--------------------|---------|-------------|---------|---------------------|
| Source      | 0.23810            | 100     | 0.9653      | 100     | 0.238080            |
| Colour1     | 0.09953            | 41.8    | 0.3207      | 33.2    | 0.099529            |
| BUN/CR      | 0.04031            | 16.9    | 0.1226      | 12.7    | 0.040311            |
| HGIB        | 0.03966            | 16.7    | 0.1322      | 13.7    | 0.039655            |
| Consistency | 0.03771            | 15.8    | 0.1240      | 12.9    | 0.037713            |
| Hematocrit  | 0.02703            | 11.4    | 0.0835      | 8.65    | 0.027025            |
| Age         | 0.01688            | 7.09    | 0.0502      | 5.20    | 0.016876            |



The figures in the boxes are the posterior probabilities when there is evidence that a patient has BUN/CR  $\geq 30$  (shown by the 100 % bar mark in the node).

Fig.2: Posterior Probability in Naive Bayesian Classifier Model When BUN/CR Is Greater or Equal to 30

We compare the original model without evidence as seen in Figure 1 with some evidence as seen in Figure 2. With evidence that BUN/CR  $\geq 30$ , the probability that a patient has UGIB rises from 39.1 % in Figure 1 to 79.8 % in Fig.2, indicating that the patient has UGIB.

**DISCUSSION**

We aimed at constructing a diagnostic model that could combine simplicity of use and high performance accuracy to allow easy application. One of the most important possible limitations of NBC use is the assumption of independence of attributes. Although in practice this assumption is not quite true, in medical applications, the NBC has been shown to be effective and gives relatively good classification accuracy in comparison with other, more elaborate learning methods. Referring to the NBC, Kononenko (1993) states that, “Physicians found such explanations (using conditional probabilities) as natural and similar to their classification. They also summed up evidence for / against a diagnosis.”

The NBC was, however, previously shown to be robust to obvious violations of this independence assumption (Domingo, 1997) and it yielded accurate classification models even when there were clear conditional dependencies. According to Rish (2001) the accuracy of the naive Bayesian model for zero-Bayes-risk problems is not directly correlated with the degree of feature dependencies measured as the class conditional mutual information between the features. Instead, a better predictor of naive Bayesian accuracy is the amount of information about the class that is lost because of the independence assumption.

In contrast with more complex models like the general Bayesian network, NBC allows for easy incorporation of additional attributes. The capability to add attributes in an easy way is a great benefit when working in fast changing fields like medicine, where new predictors may be identified. Adding new attributes or data unknown to the model may result in momentary deterioration of classification accuracy. Results improve again when the number of sample cases including new attributes increases. The NBC is also resistant to missing data i.e. with a few known attributes, one can still predict using the model e.g. if a patient is unconscious and HGIB and demographic factors like age cannot be obtained from him, a physician can still use any available data like hematocrit level to determine source of GIB. In clinical practice missing data is a common problem and a challenge to many research projects especially during classification (Quinlan, 1989). Classification results could offer valuable suggestions for the source of gastrointestinal bleeding in such difficult cases e.g. absence of hematemesis. Considering these conditions, NBC seems to be useful and deserves further study.

## CONCLUSION

The trained naive Bayesian classifier to identify the source of gastrointestinal bleeding revealed an accuracy of 87.3 %, a specificity of 0.85 and a sensitivity of 0.88. These values show the classifier's potential and credibility in supporting physicians to identify the source of bleeding in patients with GIB. The results achieved are very encouraging and they support further development of NBC as a valuable tool for supporting everyday clinical decisions.

## REFERENCES

- Al-Aidaros, K. M., Bakar, A. A., & Othman, .Z. (2012). Medical data classification with Naïve Bayes approach. *Information Technology Journal*, 11(9), 1166-1174.
- AL Dhahab, H., & Barkun, A. (2012). The Acute Management of Nonvariceal Upper Gastrointestinal Bleeding. *Ulcers*, 1-8.
- Albeldawi, M., Qadeer, M. A., & Vargo, J. J. (2010). Managing acute upper GI bleeding, preventing recurrences. *Cleveland Clinic journal of medicine*, 77(2), 131-142.
- Anderson, R. S., & Witting, M. D. (2010). Nasogastric aspiration: a useful tool in some patients with gastrointestinal bleeding. *Annals of emergency medicine*, 55(4), 364-365.
- Barkun, A. N., Bardou, M., Kuipers, E. J., Sung, J., Hunt, R. H., Martel, M., & Sinclair, P. (2010). International consensus recommendations on the management of patients with nonvariceal upper gastrointestinal bleeding. *Annals of internal medicine*, 152(2), 101-113.

- Chu, A., Ahn, H., Halwan, B., Kalmin, B., Artifon, E. L. A., Barkun, A., Lagoudakis, M. G., & Kumar, A. (2008). A decision support system to facilitate management of patients with acute gastrointestinal bleeding. *Artificial intelligence in medicine*, 42(3), 1-41.
- Crooks, C., Card, T., & West, J. (2011). Reductions in 28-day mortality following hospital admission for upper gastrointestinal hemorrhage. *Gastroenterology*, 141(1), 62-70.
- Domingos, P. (1997). On the Optimality of the Simple Bayesian Classifier under Zero-One Loss. *Machine learning*, 29(2), 103-130.
- Gralnek, I. M., & Dulai, G. S. (2004). Incremental value of upper endoscopy for triage of patients with acute non-variceal upper-GI hemorrhage. *Gastrointestinal endoscopy*, 60(1), 9-14.
- Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., & Witten, I. H. (2009). The WEKA data mining software: an update. *ACM SIGKDD Explorations Newsletter*, 11(1), 10-18.
- Hanley, A., Mcneil, J., & Ph, D. (1982). Under a Receiver Characteristic. *Radiology*, 143, 29-36.
- Jensen, D. M., Machado, G. A. (1997). Colonoscopy for diagnosis and treatment of severe lower gastrointestinal bleeding. Routine outcomes and cost analysis. *Gastrointestinal endoscopy clinics of North America*, 7(3), 477.
- Jensen, F.V., (1996). *An introduction to Bayesian Networks*. University College London press London.
- Kazmierska, J., & Malicki, J. (2008). Application of the Naive Bayesian Classifier to optimize treatment decisions. *Radiotherapy and Oncology*, 86(2), 211-216.
- Kohavi, R. (1995). A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection. *International joint Conference on artificial intelligence*, 14, 1137-1145.
- Kononenko, I. (1993). Inductive and Bayesian Learning in Medical Diagnosis. *Applied Artificial Intelligence*, 7, 317-337.
- Kovacs, T. O., Jensen, D. M. (2002). Recent advances in the endoscopic diagnosis and therapy of upper gastrointestinal, small intestinal, and colonic bleeding. *The Medical clinics of North America*, 86(6), 1315-1319.
- Kuncheva, L. I., Hoare, & Zoe, S. J. (2008). Error-dependency relationships for the Naive Bayes classifier with binary features. *Pattern Analysis and Machine Intelligence, IEEE Transactions*, 30(4), 735-740.
- Lanas, A., Garcia-Rodríguez, L. A., Arroyo, M. T., Gomollon, F., Feu, F., Gonzalez-Perez, A., Zapata, E., Bastida, G., Rodrigo, L., & Santolaria, S. (2006). Risk of upper gastrointestinal ulcer bleeding associated with selective cyclo-oxygenase-2 Inhibitors, traditional non-aspirin non-steroidal anti-inflammatory drugs, aspirin and combinations. *Gut*, 55(12), 1731-1738.
- Manning-Dimmitt, L. L., Dimmitt, S. G., & Wilson, G. R. (2005). Diagnosis of gastrointestinal bleeding in adults. *American family physician*, 71(7), 1339-1346.
- Mittal, A., & Kassim, A. (2007). *Bayesian network technologies: applications and graphical models*. IGI publishing.
- Palmer, K. R. (2002). Non-variceal upper gastrointestinal haemorrhage: guidelines. *Gut*, 51(suppl 4), iv1-iv6.
- Parkes, B. M., Obeid, F. N., Sorensen, V. J., Horst, H. M., Fath, J. J. (1993). The management of massive lower gastrointestinal bleeding. *The American surgeon*, 59(10), 676-678.
- Quinlan, J. R. (1989). Unknown Attribute Values In Induction. In *Proceedings of the sixth international workshop on Machine learning*, pp.164-168.



- Quinlan, J. R. (1993). *C4.5: Programs for Machine Learning*, volume 240 of *Morgan Kaufmann series in Machine Learning*. Morgan Kaufmann.
- Quirk, D. M., Barry, M. J., Aserko, B., & Podolsky, D. K. (1997). Physician specialty and variations in the cost of treating patients with acute upper gastrointestinal bleeding. *Gastroenterology*, *113*(5), 1443-1448.
- Rish, I. (2001). An empirical study of the naive Bayes classifier. In *IJCAI 2001 workshop on empirical methods in artificial intelligence*, volume 3, pp. 41-46.
- Tarone, R. E., Blot, W. J., & McLaughlin, J. K. (2004). Nonselective nonaspirin non-steroidal anti-inflammatory drugs and gastrointestinal bleeding: relative and absolute risk estimates from recent epidemiologic studies. *American journal of therapeutics*, *11*(1), 17-25.
- Velayos, F. S., Williamson, A., Sousa, K. H., Lung, E., Bostrom, A., Weber, E. J., Ostro, J. W., & Terdiman, J. P. (2004). Early predictors of severe lower gastrointestinal bleeding and adverse outcomes: a prospective study. *Clinical Gastroenterology and Hepatology*, *2*(6), 485-490.
- Vreeburg, E. M., Snel, P., De Bruijne, J. W., Bartelsman, J. F., Rauws, E. A., & Tytgat, G. N. (1997). Acute upper gastrointestinal bleeding in the Amsterdam area: incidence, diagnosis, and clinical outcome. *The American journal of gastroenterology*, *92*(2), 236-243.
- Wei, W., Visweswaran, S., & Cooper, G. F. (2011). The application of naive Bayes model averaging to predict Alzheimer's disease from genome-wide data. *Journal of the American Medical Informatics Association*, *18*(4), 370-375.
- Witting, M. D., Magder, L., Heins, A. E., Mattu, A., Granja, C. A., & Baumgarten, M. (2004). Usefulness and validity of diagnostic nasogastric aspiration in patients without hematemesis. *Annals of emergency medicine*, *43*(4), 525-532.
- Witting, M. D., Magder, L., Heins, A. E., Mattu, A., Granja, C., & Baumgarten, M. (2006). ED predictors of upper gastrointestinal tract bleeding in patients without hematemesis. *The American journal of emergency medicine*, *24*(3), 280-285.

