

# Machine learning can predict neutropenic sepsis in chemotherapy patients

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Background

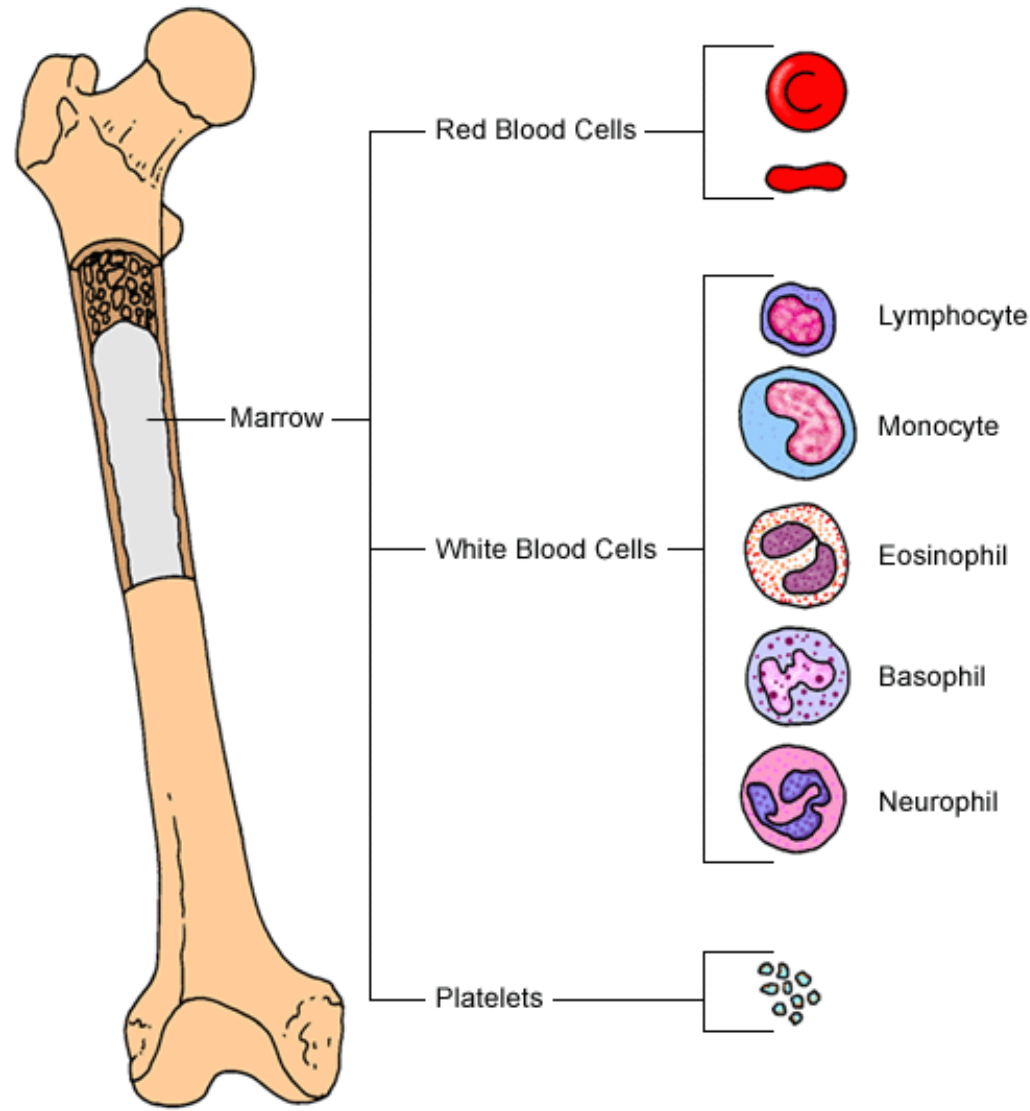
Data

Models

Results



# Febrile neutropenia and neutropenic sepsis



# Other predictive models

Original Article

## Predicting Individual Risk of Neutropenic Complications in Patients Receiving Cancer Chemotherapy

Gary H. Lyman, MD, MPH<sup>1</sup>; Nicole M. Kuderer, MD<sup>1</sup>; Jeffrey Crawford, MD<sup>1</sup>; Debra A. Wolff, MS, PCNP<sup>1</sup>; Eva Culakova, PhD, MS<sup>1</sup>; Marek S. Poniewierski, MD, MS<sup>1</sup>; and David C. Dale, MD<sup>2</sup>

**BACKGROUND:** A prospective cohort study was undertaken to develop and validate a risk model for neutropenic complications in cancer patients receiving chemotherapy. **METHODS:** The study population consisted of 3760 patients with common solid tumors or malignant lymphoma who were beginning a new chemotherapy regimen at 115 practice sites throughout the United States. A regression model for neutropenic complications was developed and then validated by using a random split-sample selection process. **RESULTS:** No significant differences in the derivation and validation populations were observed. The risk of neutropenic complications was greatest in cycle 1 with no significant difference in predicted risk between the 2 cohorts in univariate analysis. After adjustment for cancer type and age, major independent risk factors in multivariate analysis included: prior chemotherapy, abnormal hepatic and renal function, low white blood count, chemotherapy and planned delivery  $\geq 85\%$ . At a predicted risk cutpoint of 10%, model test performance included: sensitivity 90%, specificity 59%, and predictive value positive and negative of 34% and 96%, respectively. Further analysis confirmed model discrimination for risk of febrile neutropenia over multiple chemotherapy cycles. **CONCLUSIONS:** A risk model for neutropenic complications was developed and validated in a large prospective cohort of patients who were beginning cancer chemotherapy that may guide the effective and cost-effective use of available supportive care. *Cancer* 2011;117:1917-27. © 2010 American Cancer Society.

**KEYWORDS:** neutropenia, febrile neutropenia, chemotherapy, risk model.

# AUC 80%



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# Study Design

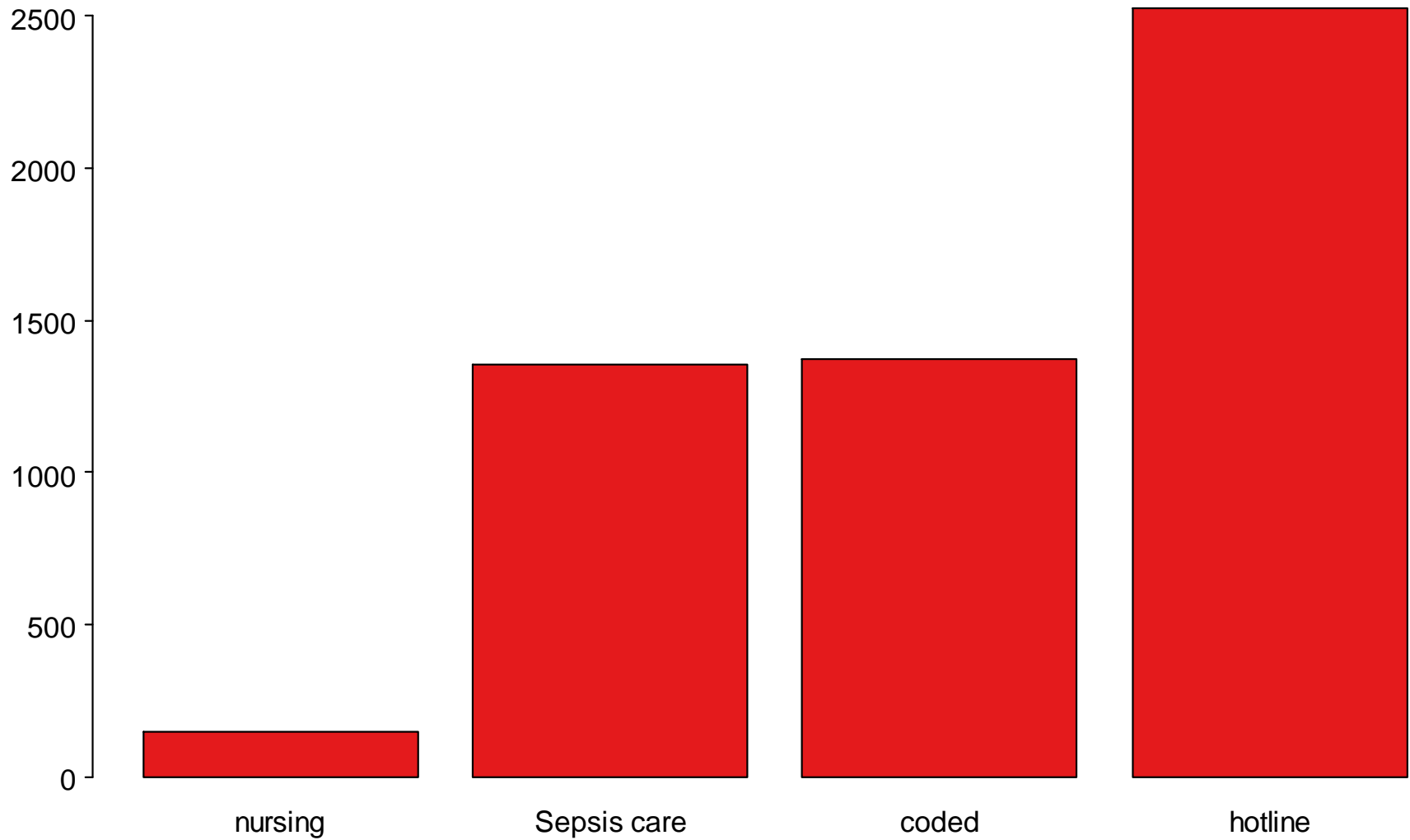


9,000 patients  
70,000 cycles  
2,500 events

4,500 patients  
15,000 cycles  
500 events



# Outcome data



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# 1,000+ binary predictors

Previous events  
Chemo regimen (350)  
Primary disease site  
Specialty  
Consultant  
Cycle number  
**Bloods**  
Comorbidities (20)  
PS  
Treatment intent  
Concurrent radiotherapy  
Stage  
Age  
Gender  
Marital Status  
Time since diagnosis  
Time of year

Calcium  
Albumin  
Alkaline phosphatase  
Aspartate aminotransferase  
Phosphate  
Potassium  
Creatinine  
Sodium  
Bilirubin  
Protein  
Gamma-Glutamyl Transferase  
Globulin  
Basophils  
Eosinophils  
Haemoglobin  
Hematocrit  
Large Unstained Cells  
Lymphocytes  
Mean Corpuscular Haemoglobin  
Monocytes  
Neutrophils  
Platelet count  
Red blood cell distribution width  
Red cell count  
White cell count



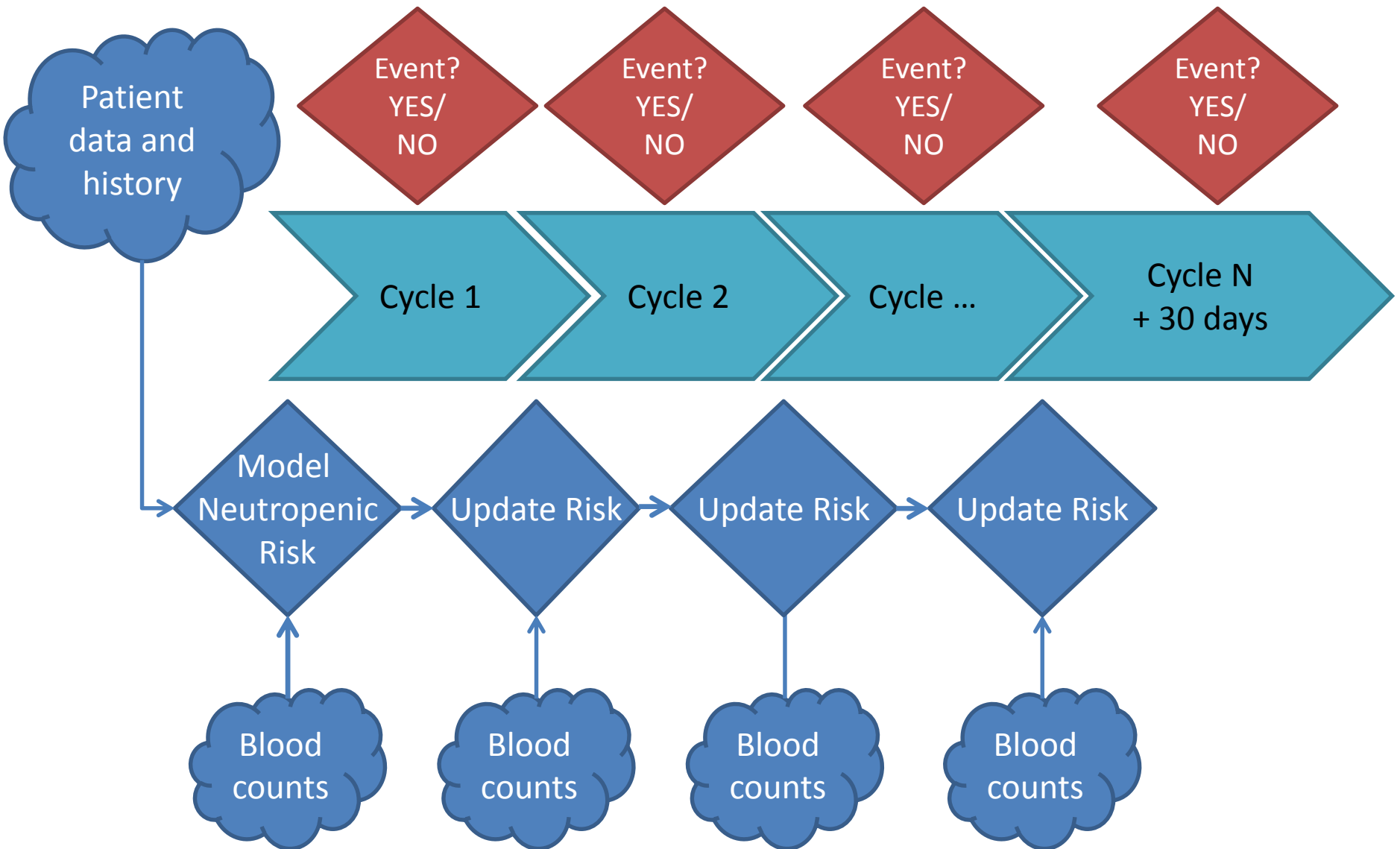
Background

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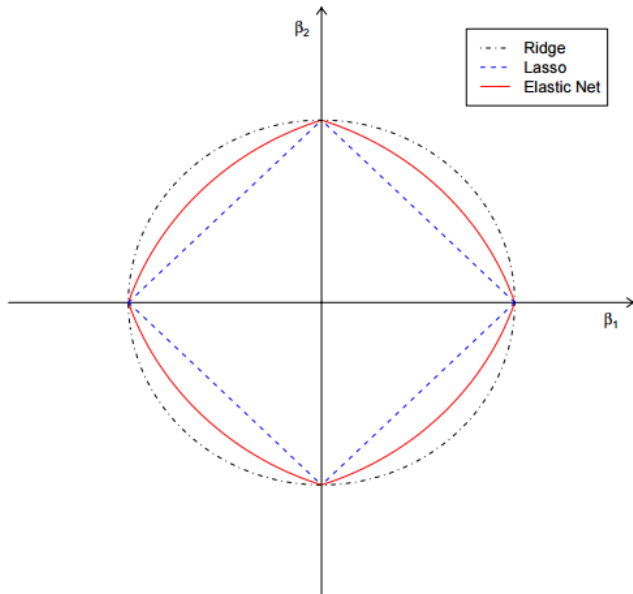
Models

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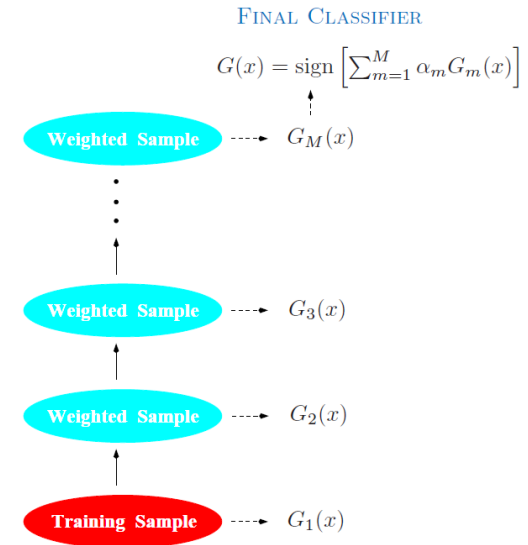
# Data Model



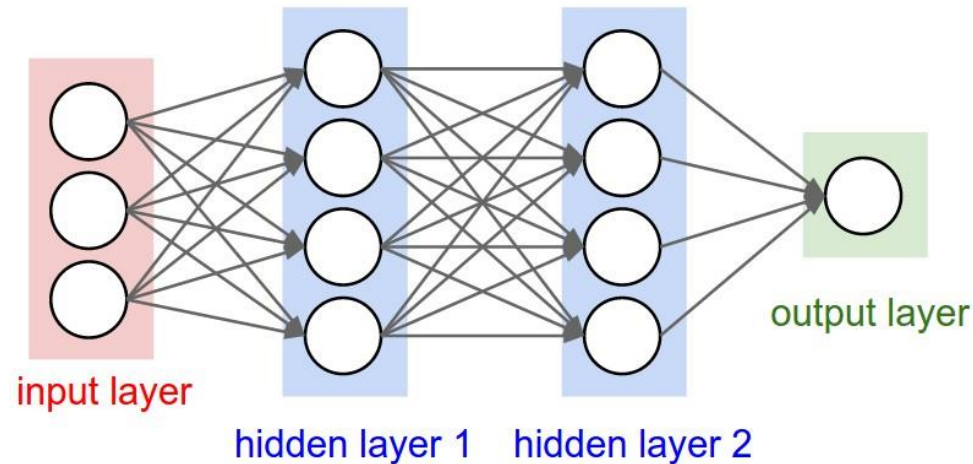
# Elastic Net



# Gradient Boosting



# Deep Neural Networks



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# Validation

Training Set  
Dec 2014 – Dec 2015

Validation Set  
Jan 2016 – April 2016

Model	AUC (%)
Deep Learning	80
Elastic Net	82
Gradient Boosting	83
<b>Ensemble</b>	<b>84</b>



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# Validation – three groups

Training Set  
Dec 2015 – Dec 2016

Validation Set  
Jan 2016 – April 2016

Risk	Neutropenic Event In Cycle		Total	P (event)
	True	False		
Low	77	8,606	8,683	1%
Medium	295	5,901	6,196	5%
<b>High</b>	<b>129</b>	<b>106</b>	<b>235</b>	<b>55%</b>
Total	501	14,613	15,114	3%
Sensitivity		Specificity		
High only	26%	99.3%		
High & Medium	85%	59%		



# Predictive application

BENJAMINSON, Arlen

Cycle start date: 2016-02-08

Risk

Risk Factors

Info

Neutropenic Risk: 74 %

30 Day Mortality Risk: 4 %

Show 10 entries

Search:

row	Casenote	First Name	Surname	Consultant	Cycle Start	Regimen	Cycle	Speciality	Neutropenic risk (%)	Days to neutropenic event	30 Day Death Risk (%)	Days to Death
83160	201519165	xxxxxx	xxxxxx	xxxxxx	2016-02-08	Brentuximab	1	Lymphoma	74	0	4.5	83160
83537	201600264	xxxxxx	xxxxxx	xxxxxx	2016-03-17	EC	1	Breast	64	1	0.6	83537
20565	201109211	xxxxxx	xxxxxx	xxxxxx	2016-02-29	Trifluridine - Tipiracil	1	GI	63	14	7.5	20565
77272	201513640	xxxxxx	xxxxxx	xxxxxx	2016-01-20	Docetaxel 100mg/m2 (21 day)	1	Breast	61	4	0.38	77272
35917	201400365	xxxxxx	xxxxxx	xxxxxx	2016-02-18	Docetaxel 75mg/m2 (21 day)	1	Prostate	59	7	5.2	35917
83224	201519227	xxxxxx	xxxxxx	xxxxxx	2016-03-18	Docetaxel 100mg/m2 (21 day)	1	Breast	59	4	0.56	83224

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# Predictive application

BENJAMINSON, Arlen

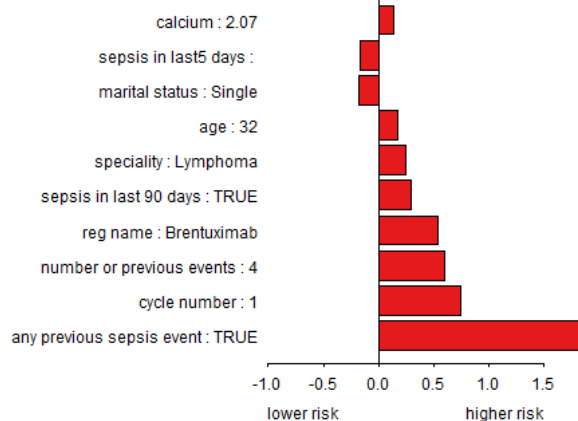
Cycle start date: 2016-02-08

Risk

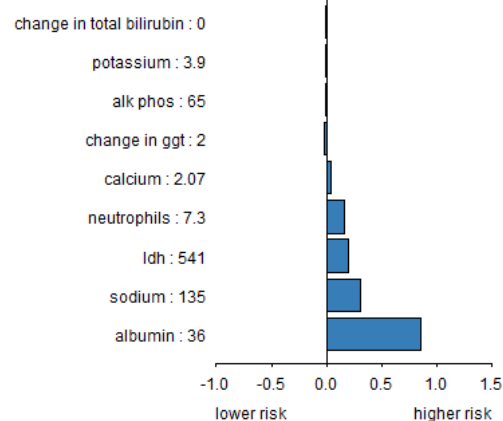
Risk Factors

Info

Neutropenic risk Factors



Mortality risk Factors



show 10 entries

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# Further work

1. Include HES outcome data
2. Plan implementation
3. Pilot feasibility study
4. Trial:
  - Cluster-randomised trial
  - Before-after prospective trial



# Conclusions

Machine learning approach was successful

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Improves accuracy of patient risk assessment

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Used routinely collected data

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Focus on improving outcome data

# Thank you

