



Applying AI-driven language models to eMRs

What can this teach us about system performance?

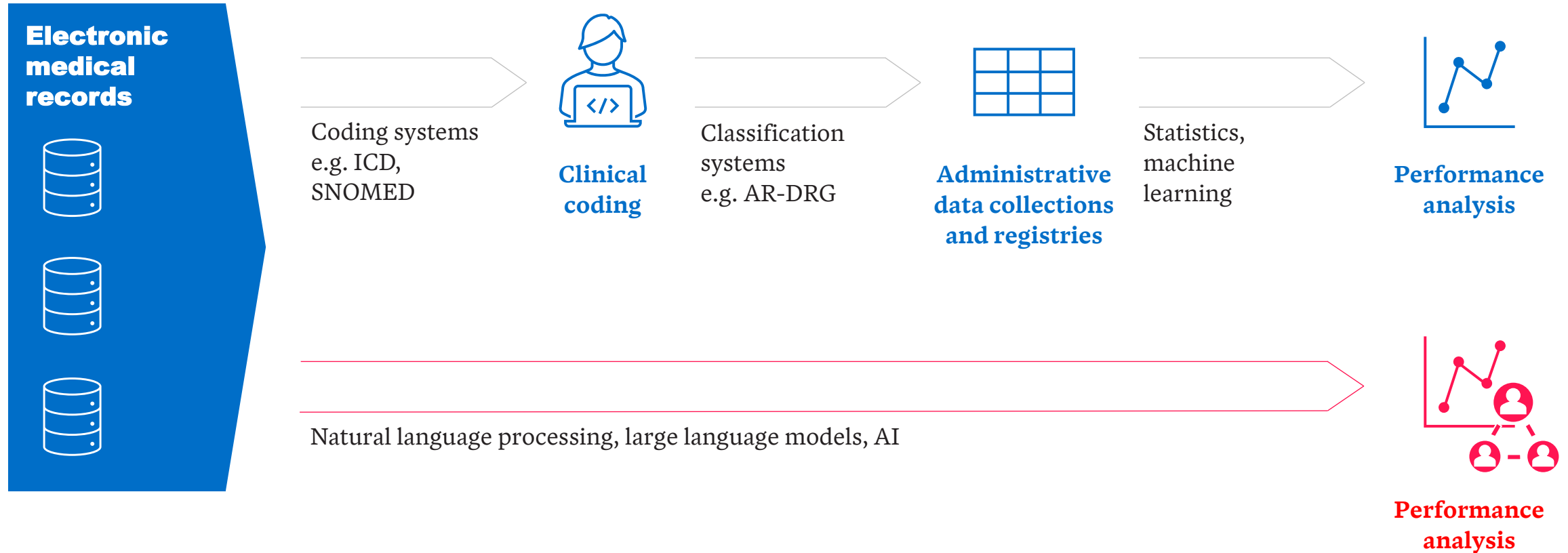
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We find the patterns that matter

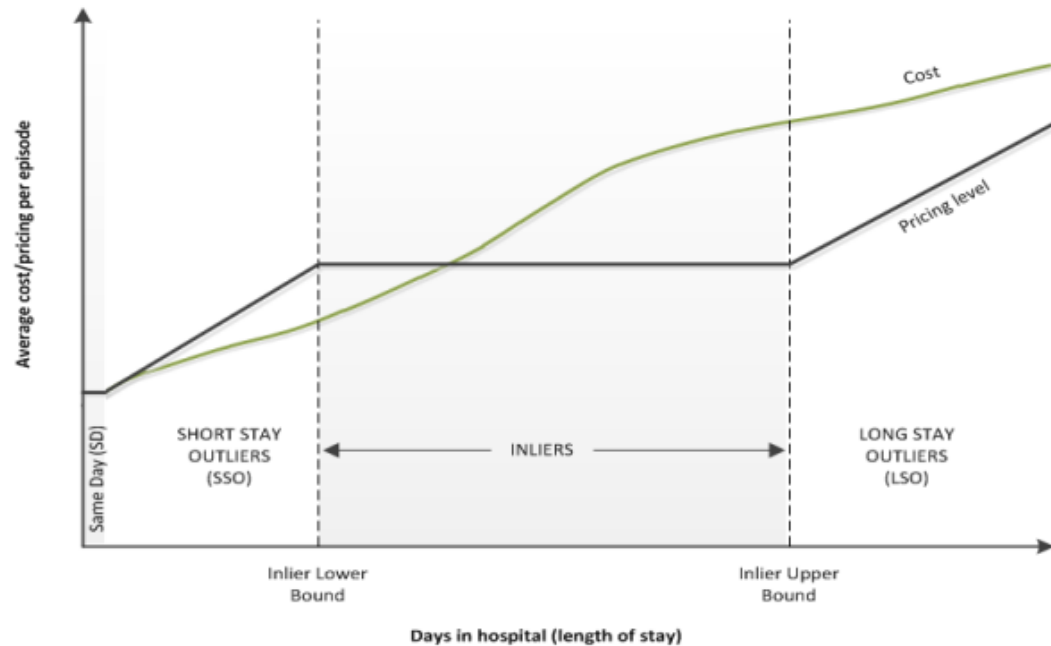


Case study: Electronic Medical Records



Activity based funding for hospital services

ABF context: pricing based on length of stay



Example model

- Can we use text information contained in an eMR to predict **higher-than-average-for-DRG LoS**?
- What information can these models provide about **what drives LoS** over and above existing classification systems?

Source: IHACPA, National Pricing Model Technical Specifications

Deriving insights from eMR data

An eMR dataset: MIMIC III

- Medical Information Mart for Intensive Care (MIMIC)
- Publicly available, de-identified dataset of 50,000 ICU patients at the Beth-Israel Deaconess Medical Centre in Boston, Massachusetts, USA



MIMIC III dataset – hospital data

ICU

MICU SICU CCU CSRU NICU

Bedside monitoring



- Vital signs
- Waveforms
- Trends
- Alarms

Chart



- Fluids
- Medications
- **Progress notes**

Tests



- Laboratory
- Microbiology

Orders



- Provider order entry (POE)

Billing



- ICD9
- DRG
- Procedures (CPT)

Demographics



- Admission & discharge dates
- Birth & death dates
- Religion
- Ethnicity
- Marital status

Notes & reports



- **Discharge summaries**
- Radiology (X-ray, CT, MRI, Ultrasound)
- Cardiology (ECHO, ECG)

Modelling longer length of stay (LoS)

We compare 5 models of **likelihood of longer than average-for-DRG LoS**:

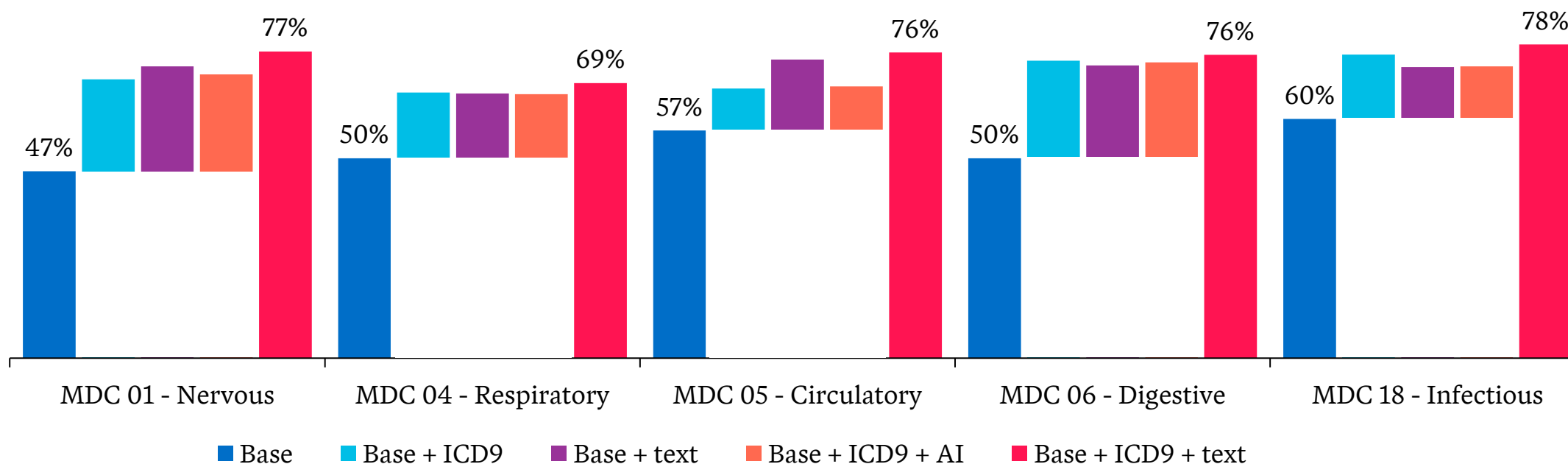
Base model	Base + ICD9	Base + text	Base + ICD9 + text	Base + ICD9 + AI
<ul style="list-style-type: none">▪ Age▪ Sex▪ Insurance status	<ul style="list-style-type: none">▪ Base variables▪ Top 10 ICD9 procedures and top 10 ICD9 diagnoses for each MDC	<ul style="list-style-type: none">▪ Base variables▪ Discharge summary, nursing and physician notes	<ul style="list-style-type: none">▪ Base variables▪ Top 10 ICD9 procedures and top 10 ICD9 diagnoses for each MDC▪ Discharge summary, nursing and physician notes	<ul style="list-style-type: none">▪ Base variables▪ Top 10 ICD9 procedures and top 10 ICD9 diagnoses for each MDC▪ Discharge summary, nursing and physician notes
Structured data only		Models include clinical notes analysis		
Regression		Regression + Term Frequency / Inverse Document Frequency (TF/IDF) model		Regression + Bio-Clinical BERT model

Note: All regression models are L1-regularised (LASSO)

Modelling longer length of stay (LoS)

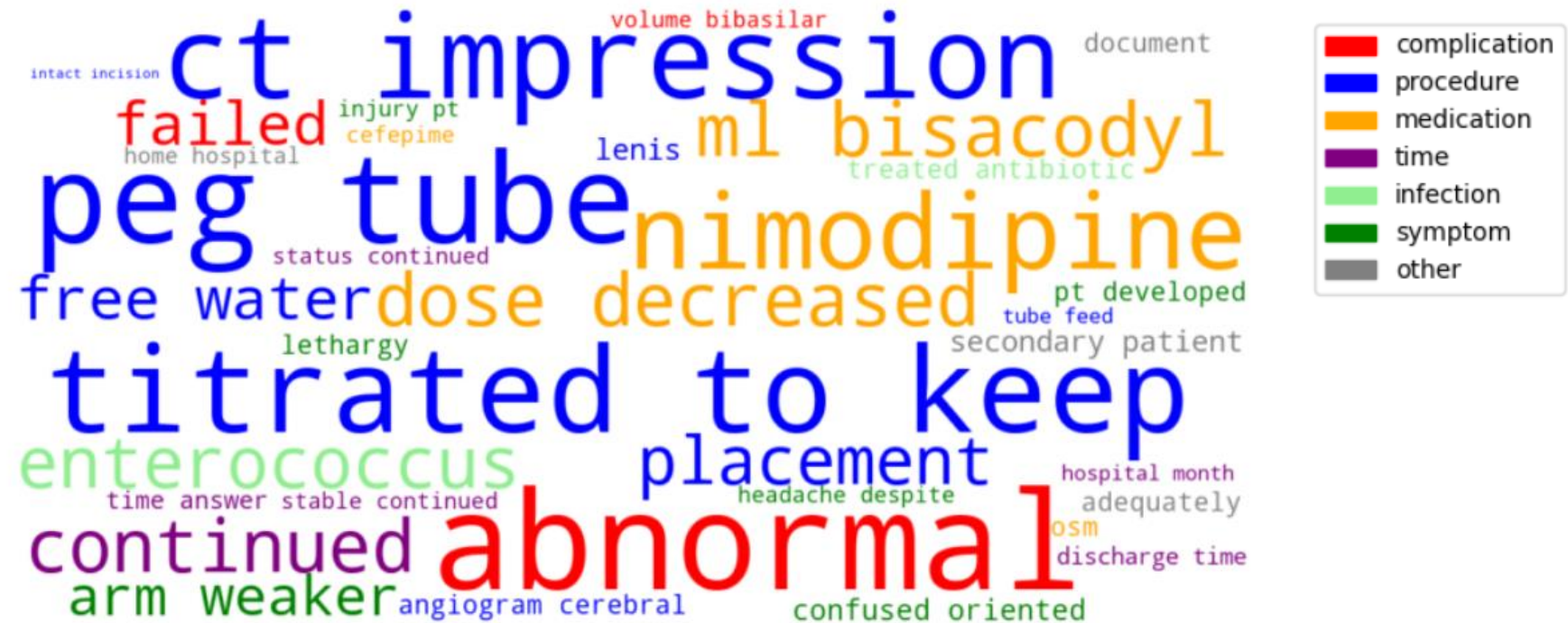
- **Base + ICD9 + text performs best** at predicting longer LoS episodes
- Adding text on its own has similar explanatory power to adding ICD9 diagnoses and procedures

Model performance – AUC on a hold-out test set



What contributes to longer LoS, after controlling for comorbidity?

Text features for MDC 01 – Diseases and disorders of the nervous system
Base + IDC 9 + text model



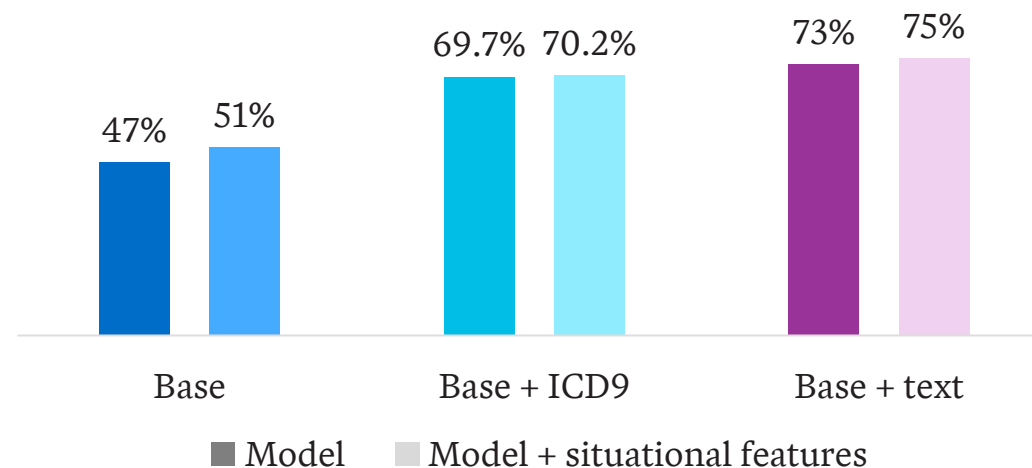
What if we “direct” the models for where to look?

Feature engineering can help improve model performance and “direct” the models to put explanatory power into features we expect to have an impact

**Socio-economic and trauma-related
features created from text**



**Model performance
AUC for MDC 01 - Nervous system**



How can we use these models to monitor performance?



Zoom out

- Develop models on a broader range of eMR data
- Compare results from **multiple facilities to highlight unaccounted-for variation** in case-mix and care



Zoom in

- The models can be powerful in identifying **patterns in care pathways**, e.g. whether best-practice protocols are followed after a procedure
- Must be **purpose built, collaborating with clinicians** to identify key metrics



Enrich

- The models can be used to **incorporate additional information, such as socio-economic information**, about case mix that isn't covered by current classification systems, but does explain differences in efficiency

Evaluate

- **Evaluate the models prior to implementation** to choose most suitable: don't use AI for the sake of AI!
- **Monitor the models** to ensure they are still performing as the environment changes



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