

# ConCare: Personalized Clinical Feature Embedding via Capturing the Healthcare Context

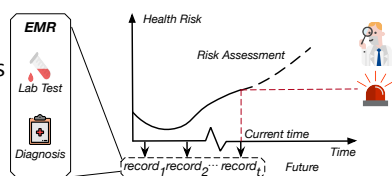
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SCAN ME!

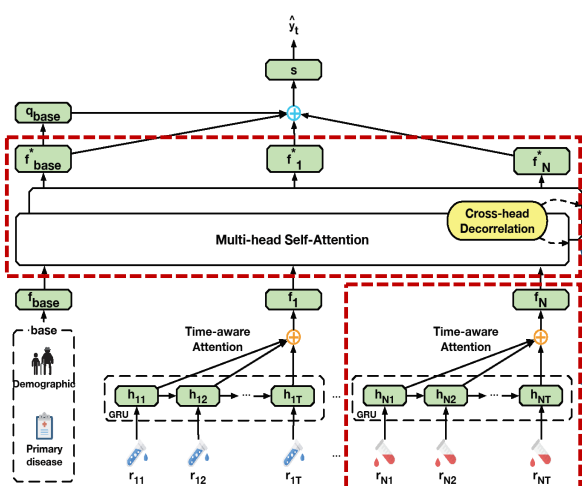
## I. Background

- By evaluating patient's health status **comprehensively**, physicians can:
  - ✓ Select follow-up personalized treatments
  - ✓ Prevent adverse outcomes
  - ✓ Assign medical resources effectively
  - ✓ Reduce the medical cost
- Practical application:**
  - ✓ Prognosis of End Stage Renal Disease (ESRD)



## II. EMR Data

- A type of multivariate time series data that records patients' dynamic visits and static baseline information.
- Static Information:**
  - ✓ Demographics (Age/Gender/...)
  - ✓ Primary diseases (Diabetes/...)
- Dynamic Information:**
  - ✓ Lab test results (Blood glucose/...)

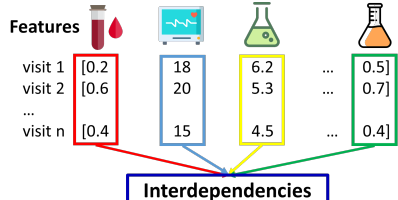


## III. Framework of ConCare

We propose a multi-channel healthcare predictive model, which can learn the representation of health status and perform the health prediction by more deeply considering the personal health context.

- Take the embedding of all features as healthcare context.
  - ✓ The feature encoder is adopted to combine all the static information and dynamic records based on **self-attention**, and learn **interdependency among features**.
- Capture the impact of time interval for different features.
  - ✓ The multi-channel time series embedding module with **time-aware attention** is developed to separately learn the representation of each dynamic feature.

### Insight 1: Extract Personal Health Context (Feature Interdependency)

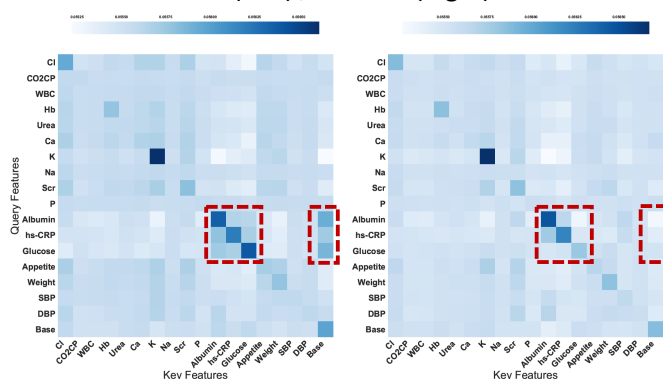


- A certain value of a clinical feature (e.g., blood glucose) may imply different meanings to patients with diverse static baselines (e.g., diagnosis of diabetes as a primary disease).
- We explicitly extract interdependencies between clinical features to learn the personal health context and regenerate the feature embedding under the context, by a **multi-head self-attention mechanism**.

### Case study on experiment:

- Most of the clinical features are more likely to respond to themselves, which is denoted by the diagonal of two matrices.
- By comparing the two figures, in the box of **Glucose-Glucose** position, the model pays much more attention to the glucose in **patients with diabetes**.
- Besides, there are relatively high interdependencies between **blood albumin, hyper-sensitive C-reactive protein (hs-CRP), glucose and the static baseline information (including the diagnosis of diabetes)** for patients with diabetes.

### Cross-Feature Interdependency: Patients with (Left) / without (Right) Diabetes



This is consistent with the medical research and clinical experience.

### Insight 2: Capturing the Impact of Time Interval for Different Features

- It is usually assumed that the more recent clinical records weight more than previous records.
  - ✓ The historical record of serum potassium several years ago has little influence on current healthcare prediction.
- However, historical records also contain valuable clinical information, which may not be revealed in the latest record.
- We learn the representation of different feature sequences via separate GRUs, and adaptively captures the effect of time intervals between records of each feature **by time-aware attention**.

### Case study on experiment: Time-decay rates for different features

- ConCare attends more on the **short-term of serum creatinine (Scr), potassium (K), white blood cell count (WBC), calcium (Ca), carbon dioxide combining power (CO2CP), chlorine (Cl), hemoglobin (Hb)**. They are relatively fast changing indicators, reflecting patients' infection status or dialysis adequacy, etc.
- ConCare attends more on the **long-term of Body Weight, Albumin, Na and systolic pressure (SBP)**. They are usually related to nutrition intake and reflect the patient's condition over a period of time.

