# CARBONIC ANHYDRASE: KINETICS OF REMOVAL OF Zn(II) By 2,6-PYRIDINECARBOXYLATE

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**Abstract**

In the past decade, supervised activity recognition methods have been studied by many researchers, however these methods still face many challenges in real world settings. Supervised activity recognition methods assume that we are provided with labeled training examples from a set of predefined activities. Annotating and hand labeling data is a very time consuming and laborious task. Also, the assumption of consistent pre-defined activities might not hold in reality. More importantly, these algorithms do not take into account the streaming nature of data, or the possibility that the patterns might change over time. In this chapter, we will provide an overview of the state of the art *unsupervised* methods for activity recognition. In particular, we will describe a scalable activity discovery and recognition method for complex large real world datasets, based on sequential data mining and stream data mining methods.

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# Introduction

Carbonic anhydrase (CA) catalyzes the interconversion of carbon dioxide and carbonic acid/bicarbonate as follows:

$$CO_2 + H_2O \xrightleftharpoons{\text{CA}} H_2CO_3 \tag{1}$$

In the active form, CA is bound to a $Zn^{2+}$ cofactor (denoted as CA•Zn), which it relies upon for its catalytic activity. The zinc ion can be stripped from the enzyme using a lewis base ligand, which donates electrons to the ion to form a covalent bond. The ligand being studied in this experiment is 2,6-pyridinecarboxylate, commonly called dipicolinate (or dipic). Figure 1 shows the structure of dipic. In this experiment, the rate of zinc removal by dipic will be measured.

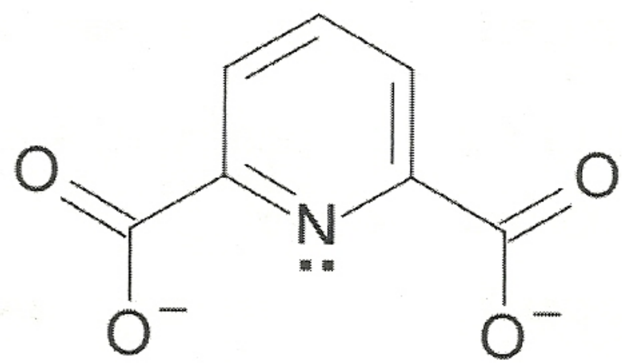

Figure 1: Structure of 2,6-pyridinecarboxylate (dipic)[1]

## Mechanism

When $[dipic] >> [CA]$, that is, when $\frac{[dipic]}{[CA]} \geq 25$, then the reaction is pseudo-first-order with respect to

## Data and Results

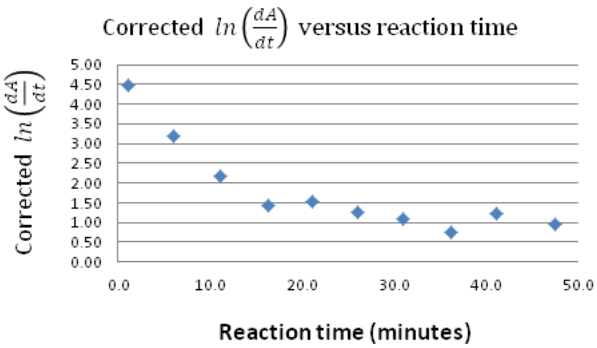


Figure 2: laksjdf askdfj asdkljfhaslkdjfhaklsdjfh asldkfjhasdlkjfhalksdjfhalksdjfh asldkfjhasdlkfjashdlfkajsdhflkajshdf asdfa sdiufhaisdu fas dfasd fasef asefasef asefas efasefkahsdkjfhaskldjfha sdfasldkfjhasdlfkjasdh falksdjfhalskdjfhasdlkfjah sdflkjashdlkfjah sdlkfjh aslkdjfh aslkdjfhalksdjfhalksjdh flkajsdhf alsdkjfash dflaskdjfah .

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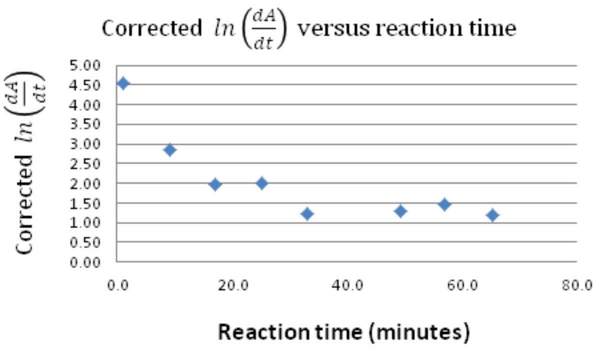


Figure 3: blahblah.

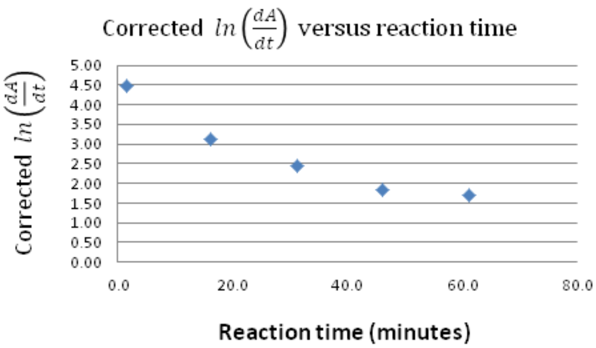


Figure 4: blahblah.

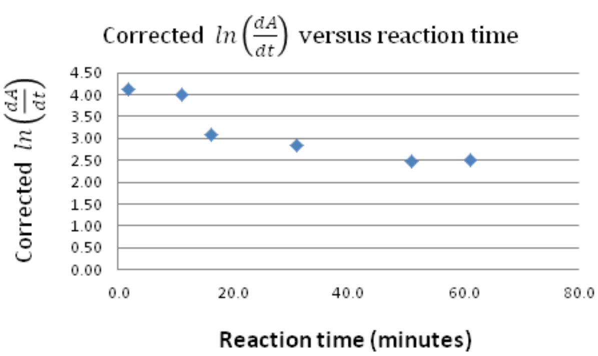


Figure 5: blahblah.

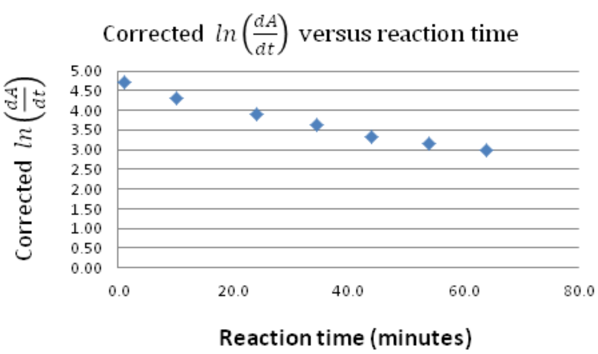


Figure 6: blahblah.

## References

(1) Killian, B. J. *Experiments for Physical Chemistry Laboratory*, Summer 2014, Target Copy: Gainesville, **2014**. 45 - 50.