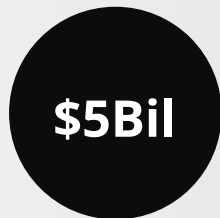




Augusta 2.0 Overview

How does AI ML benefit health systems and hospitals?

- Diagnose disease more accurately
- Improve care delivery and personalized medicine
- Align hospital reporting and administration to VBC incentives
- Effectively plan treatments



Value in preliminary diagnosis



Cost to bring a single drug to market

Estimated potential annual benefit for an application by 2026. Source: Accenture analysis, "AI: Healthcare's New Nervous Systems" (2017).

POTENTIAL BENEFITS

30 TO 40% IMPROVED DIAGNOSIS

- Millions of Americans are misdiagnosed annually, e.g. ~12 million with incorrect diagnoses in outpatient clinics in 2014 (CBS News).
- Potential to improve diagnostic outcomes by 30% to 40%.
- Potential to reduce hospital stays, unnecessary readmissions and testing, and health care costs.

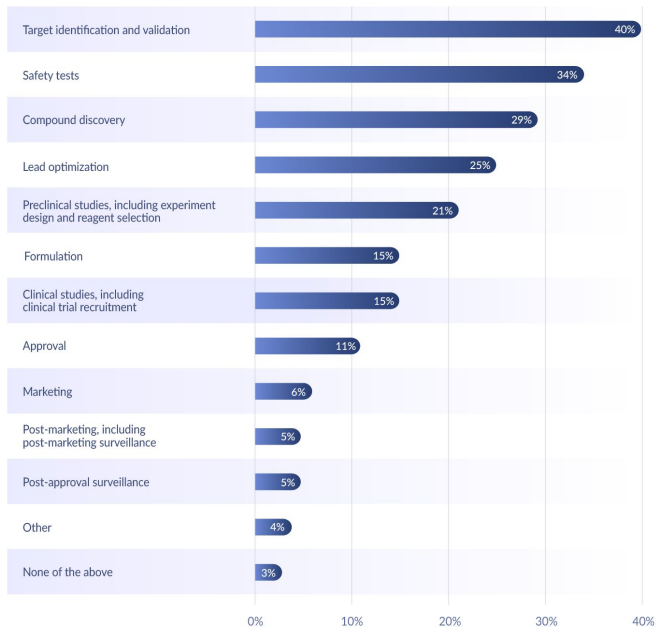
Source: Frost & Sullivan, "AI & Cognitive Computing Systems in Healthcare" (December 2016). TM Capital Industry Spotlight, "The Next Generation of Medicine: AI and Machine Learning" (2017).



Current State of AI Adoption - Heavily Verticalized



For what stages of drug discovery does your organization currently use artificial intelligence?



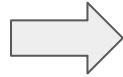
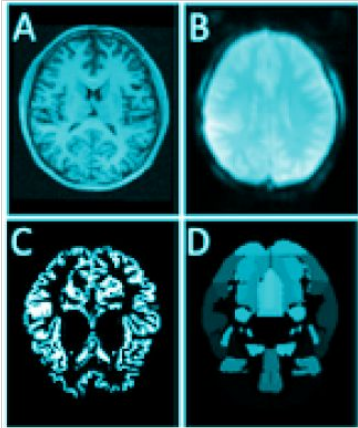
A recent survey of the Drug Discovery industry found that most current applications of AI are in areas you might expect (target identification, safety, discovery)

Most identified “Speed of Discovery” as the greatest motivating factor for using AI, however, **45% thought their application of AI would remain the same next year**

The Problem With Verticalized Applications of AI



- Our initial model showed a marked difference between control and disease groups, however this was only due to an undetected bias in survey site



Control Patients (Avg)



Autistic Patients (Avg)

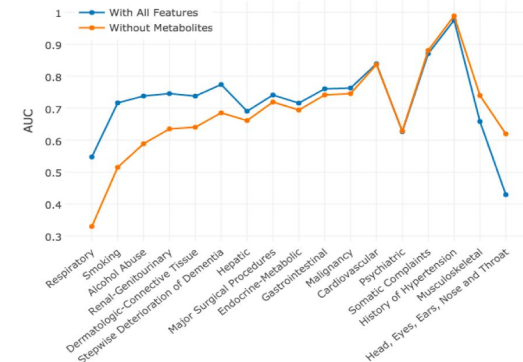
Integrating Data for Better Accuracy



- Combining MRI with genomic features allowed **better prediction performance** than with either alone - Alzheimer's Disease Neuroimaging Initiative (ADNI) data

Evaluation Metric	MRI	Metabolomics	Genetics	All combined
True Positive Rate	0.73	0.73	0.77	0.83
False Positive Rate	0.66	0.63	0.5	0.39
AUC	0.56	0.55	0.68	0.73

- This combination approach becomes more accurate as additional data types are included, and is **effective in precision medicine & drug discovery applications**



What Limits the Widespread Application of AI in Biomedicine?



Data Variety/Heterogeneity

Different Data Types:
EHR/EMR, MRI/fMRI,
EEG, EKG, chemistry

**Single framework for
integration of diverse
data types**



Lack of Standards

No standards for
processing or interpreting
medical data

**Dynamic, optimized
pre-processing**

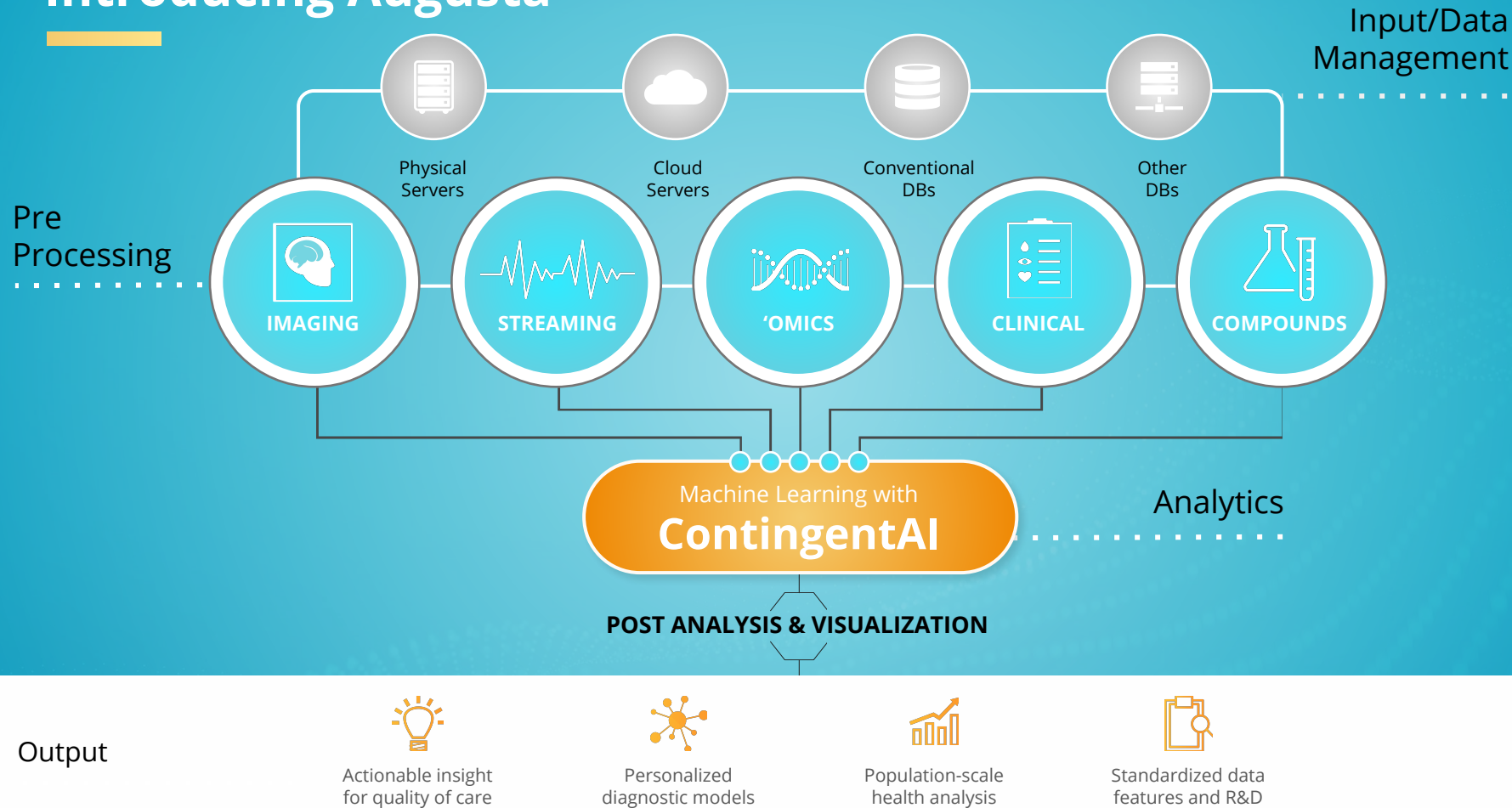


Lack of Scalability

Challenges in pre-processing
and machine learning using
massive data

**Deploy anywhere, on
any architecture**

Introducing Augusta



The diagram illustrates a machine learning pipeline for medical image analysis, organized into three main stages: PRE PROCESSING, FEATURE SELECTION, and MACHINE LEARNING. Each stage contains several sub-steps, represented by yellow circles. Orange lines indicate the flow and dependencies between these steps.

- PRE PROCESSING**
 - Pixel threshold
 - Linear/nonlinear reg
 - Volume threshold
 - Smoothing methods
- FEATURE SELECTION**
 - Number of features
 - Transformation alg. (PCA, ICA, etc)
- MACHINE LEARNING**
 - ML Model (SVM, RF, NN, etc)
 - Model Parameters

A **RESULT** box is shown on the right. Orange lines connect the 'Transformation alg.' step to the 'ML Model' and 'Model Parameters' steps, indicating a flow or dependency.

PRE PROCESSING

Pixel threshold

Linear/nonlinear reg

Volume threshold

FEATURE SELECTION

Smoothing methods

Number of features

Transformation alg. (PCA, ICA, etc)

MACHINE LEARNING

ML Model (SVM, RF, NN, etc)

Model Parameters

RESULT

RESULT

What Makes Augusta Unique?



Augusta is a single language that you can use to process and interpret biomedical data, allowing you to build automated AI workflows

PRE PROCESSING

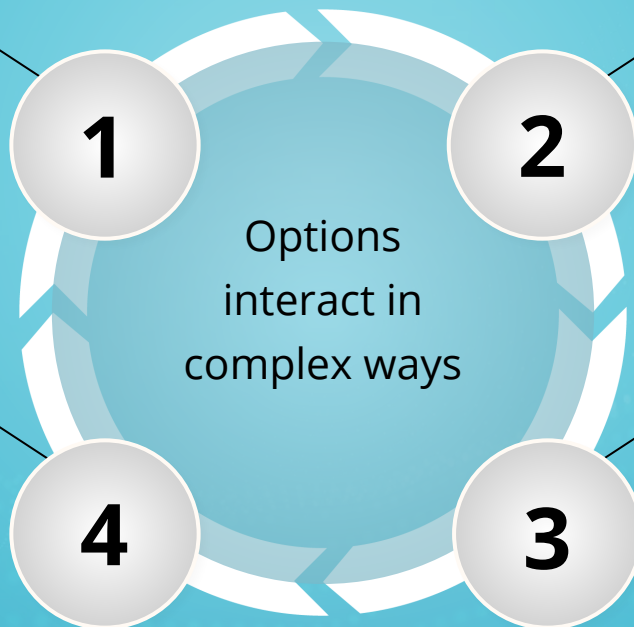
Options/Parameters:

- Pixel threshold
- Linear/nonlinear reg
- Volume threshold
- Smoothing methods

EVALUATION

Options/Parameters:

- Criteria
(AUC, sensitivity, specificity,
network overlap, etc)



FEATURE SELECTION

Options/Parameters:

- Number of features
- Transformation alg.
(PCA, ICA, etc)
- Selection alg.
(Backwards elim, MI)

MACHINE LEARNING

Options/Parameters:

- ML model
(SVM, RF, NN, etc.)
- Params of each

Augusta 2.0 - A Biomedical AI Language



All operations are treated as optimizable blocks:



Source - Data source (file, directory of files)



Transform - Data transformation, such as a preprocessing step for a specific datatype (e.g. skull subtraction for an MRI) or an operation (e.g. calculating a mean)



Model - Any number of machine learning models



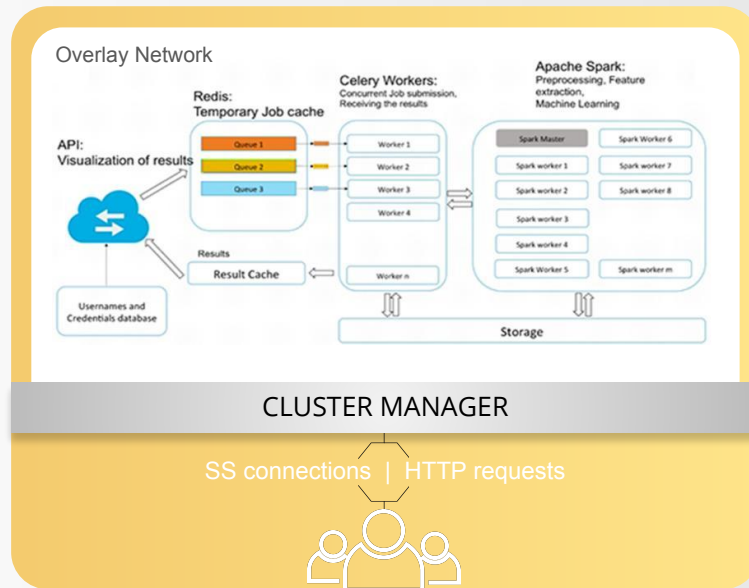
Performance - Examine impact of transformation & model parameters

How the Augusta™ Platform Works

Augusta™ can start with siloed, complex, and raw data of multiple types:



- Integration of diverse and large-scale data types
- Data of any type, size, and dimensionality explored and modeled
- Biological, clinical, genomics, precision medicine, metabolomic, lab testing, drug compound data



- Accurate results and automated distribution
- Built for massive data architecture
- End-to-end machine learning
- Post-analysis & data visualization

Our Partners and Market Environment



PLUGANDPLAY



sema4



DRUG DISCOVERY

Reduction of Chemical Survey Space
Prediction of Molecular Mechanism
Experimental Data Integration



PRECISION MEDICINE

Genomic Risk Assessment
Improved Disease Diagnosis
Patient Data Integration



VALUE-BASED CARE

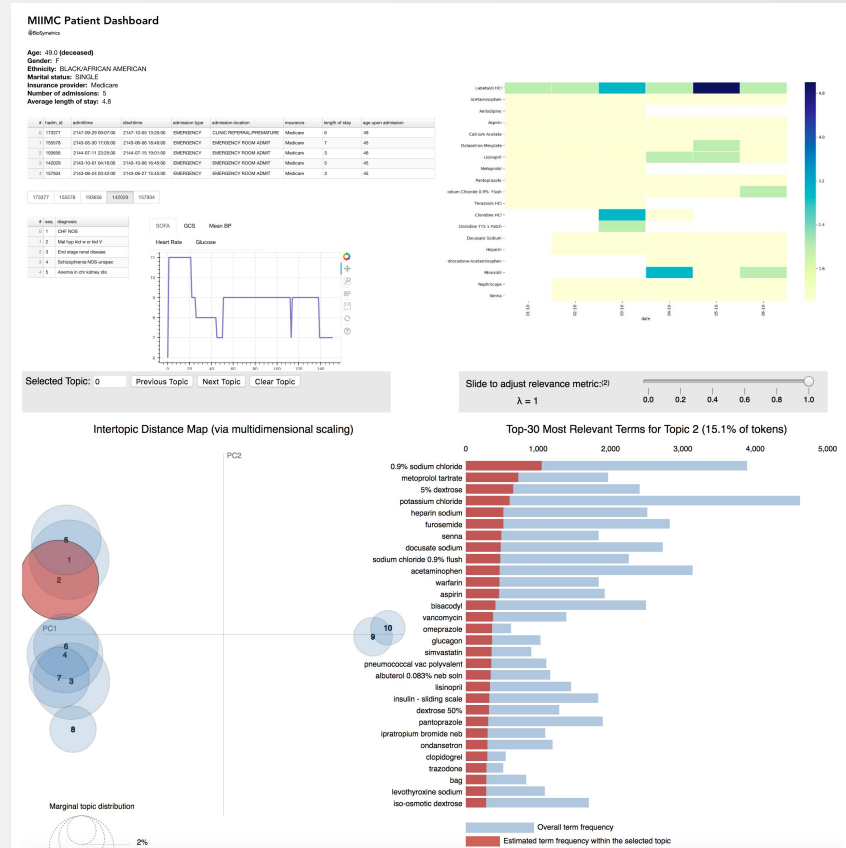
Patient stratification
Outcome & Event Prediction
Operational Analysis



Use Cases: Outcomes Prediction



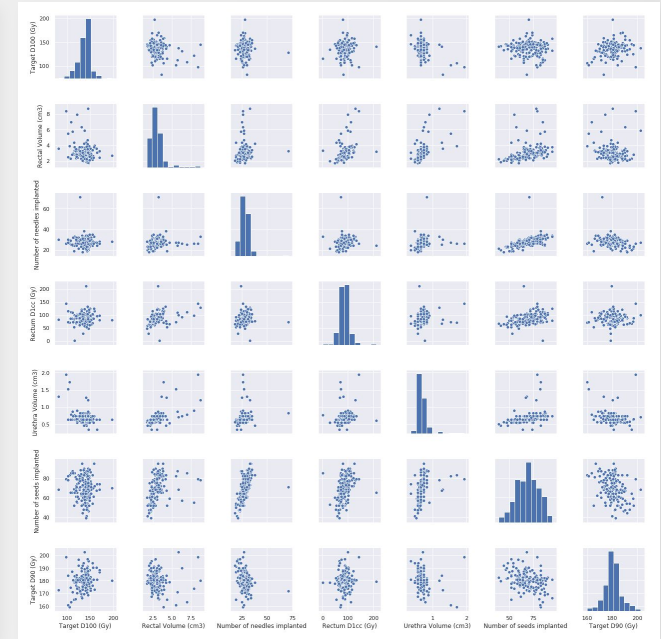
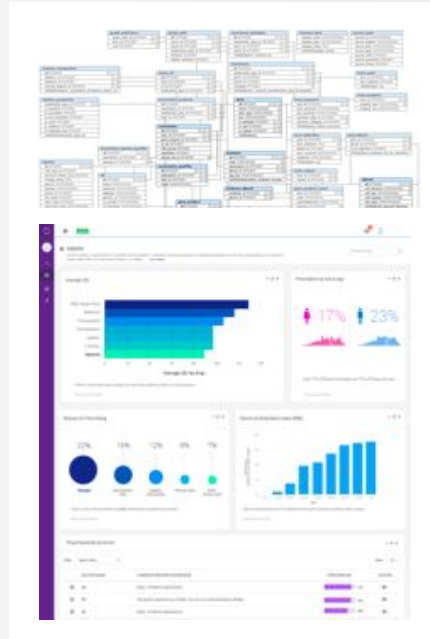
- Continuously updated calculation of severity scores (including SOFA)
- Generate dynamic risk scoring for patients using time-based models
- Symptoms extracted from clinical notes
- Prescription names mapped to relevant MeSH terms, allowing systematic analysis of prescriptions by type



Use Cases: Value Based Care



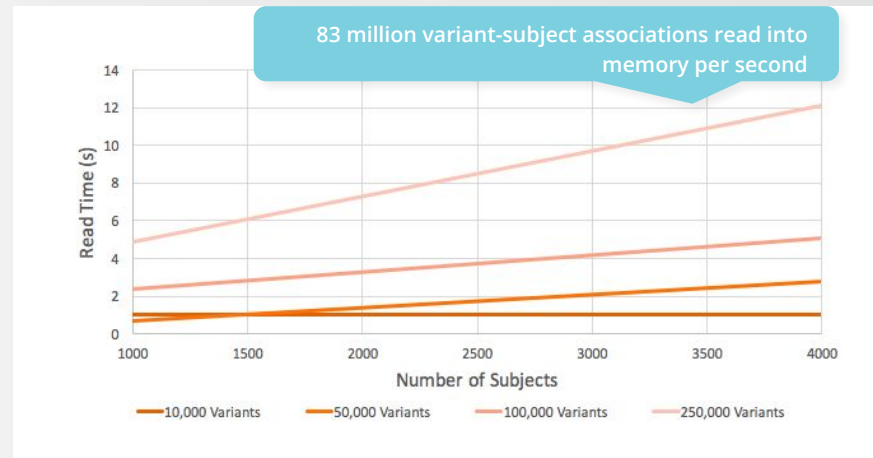
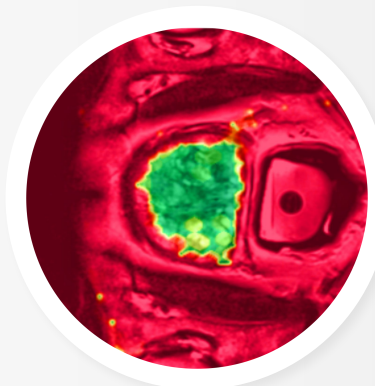
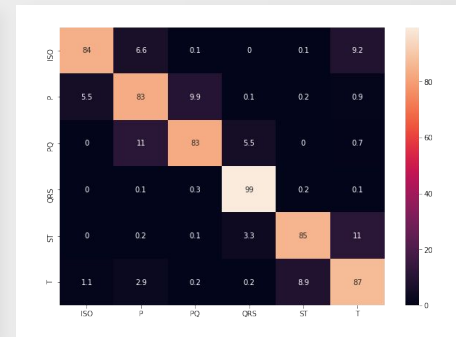
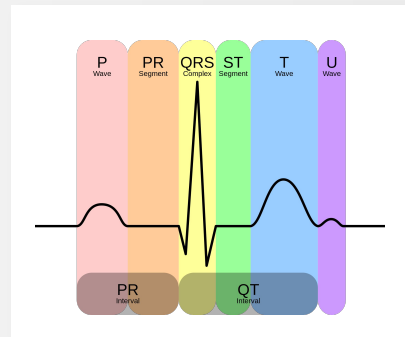
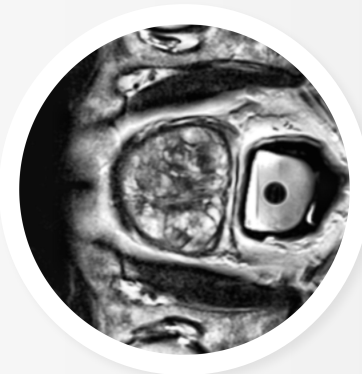
- GE Healthcare (US) major initiative in value based care, predicting outcomes for patients with chronic conditions (NLP-based)
- OrbCare (Canada) analysis of clinical billing to identify diagnostic code over/under use
- Intacare (UK) homogenization of billing codes



Use Cases: Precision Medicine



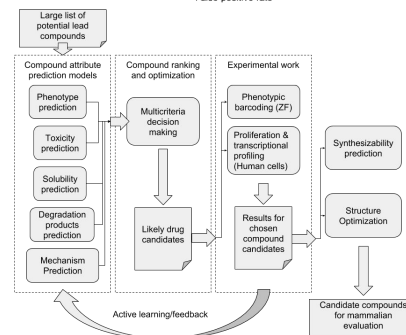
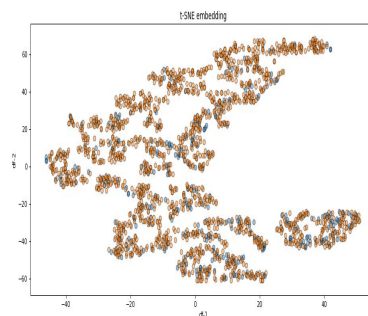
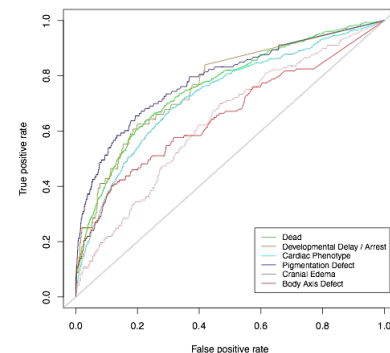
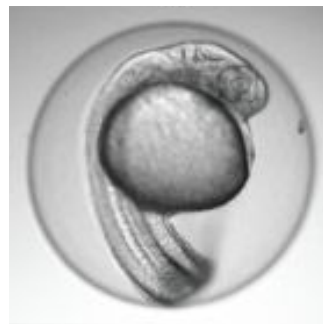
- Automatable, dynamic processing of medical images & streaming data from virtually any format
- Easy integration of multiple lines of clinical data
- Scalable model generation using cloud and conventional computing



Use Cases: Drug Discovery & Building an Automated Platform



- Initial models focused on predicting zebrafish phenotypes
- Prioritized compounds showed correlates in clinical application
- In a collaborative effort, we included genomic, proteomic, and transcriptional data, generating predictions of molecular mechanism underlying phenotypes
- Currently working to automate this process:
 - Begin with prediction of phenotype
 - Automated phenotypic barcoding
 - Predict molecular mechanism & validate
 - Refine process



Our Team



Anthony Iacovone

**Co-Founder & Board
Chairman**



Gabriel Musso, PhD

Chief Scientific Officer



Wendy Tsai, MBA

**VP Business
Development**



Babak Afshin-Pour, PhD

VP of Technology



Victoria Catterson, PhD

Principal Data Scientist



Cindy Lopes

**Application
Developer**



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www.biosymetrics.com | [Twitter @biosymetrics](https://twitter.com/biosymetrics)

CONTACT

Wendy Tsai | VP Business Development | wendy@biosymetrics.com

Gabe Musso | Chief Scientific Officer | gabe@biosymetrics.com