ALLYTALK



Al-Driven Clinical Analytics: Turning Complex Oncology Data into Actionable Insights

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Disclosure



Scott Newman works for

Meaningful Insights | BioTech Analytics
(MiBA), a company that provides data
services to community oncology and
biopharma partners





The patient is at the center of everything that we do but ...





But what is their:

Diagnosis

Stage

Grade

Histology

Labs

The patient is at the center of everything that we do but ...

Diagnosis date

Comorbidities

Metastatic status

NGS Results

Procedures

Adverse events Medications ...





20% of patients being treated for cancer within the MiBA network don't have staging information readily available





Problem 1: There is a high degree of 'missingness' for nearly every important piece of information





Problem 2: It is challenging to see the entire patient journey as the data is spread across systems





We need a complete and accurate patient journey to do almost anything in the oncology analytics space



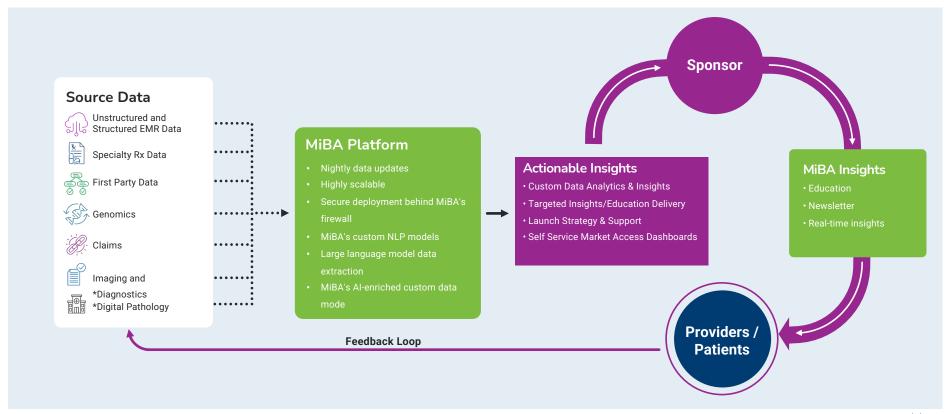


The Solution: An Al-augmented and holistic oncology data model





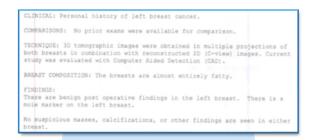
Data Production Line







Natural Language Processing Mines Clinic Notes and PDFs



PDFs, scans and raw note text

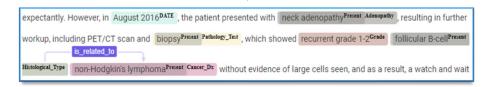
CLINICAL: Personal history of left breast cancer.

COMPARISONS: No prior exams were available for comparison.

TECHNIQUE: 3D tomographic images were obtained in multiple projections of both breasts in combination with reconstructed 2D (C-view) images. Current study was evaluated with Computer Aided Detection (CAD).

BREAST COMPOSITION: The breasts are almost entirely fatty. FINDINGS: There are benign post operative findings in the left breast. There is a mole marker on the left breast. No suspicious masses, calcifications, or other findings are seen in either breast.

Computer-readable text



NLP model extracts 'entities' and 'relationships'





Large Language Models Go a Level Deeper

False Positive by NLP:

 Discussed the implications of a positive ROS1 result. She continues on immunotherapy until NGS testing comes back ...

False Negative by NLP:

 [NGS] testing showed a TKI fusion. Anti-ROS1 therapy, started

ROS1 negative by LLM

ROS1 positive by LLM





All Data Feeds in a Single Unified Model

Table Name	Table Description
patient	Information about patients in the dataset
cancer_dx	Information about patient's cancer diagnoses. Each row represents one primary cancer diagnosis for the patient
cancer_dx_biomarkers	Extension table for cancer_dx. Table containing biomarker results linked to each cancer diagnosis, joinable to the cancer_dx table on patient_id and cancer_group_name
cancer_dx_diagnostic_factors	Extension table for cancer_dx. Table containing cancer- specific diagnostic factor results linked to each cancer diagnosis, joinable to the cancer_dx table on patient_id and cancer_group_name
comorbidities	Additional diagnoses for other diseases assigned to patients
icd10_codes	Table of all ICD10 codes assigned to the patient, and in whic context and with earliest and latest assignment dates
ecog_status	Patient's ECOG Status history, with the most recent ECOG Status flagged
pain_scores	Patient history of Pain Score reporting. Includes date, scale used, and provided pain score
genetic_results	Patient genetic results obtained from NGS testing. Includes short variants, copy number variants, and fusions. Also links to cancer_dx via patient_id and cancer_group_name, where available
lab_results	Patient lab results, mapped to LOINC code. Containing cleaned, mapped values as well as underlying (source) data
vital_signs	Vital sign history for the patient. Includes weight, height, temperature, O2 Saturation, pulse, and others
medications	Patient medication history, including date of drug record and mappings to cleaned generic and branded drug names
lines_of_therapy	Description of drug lines patients have taken, mapped to individual cancer diagnoses
procedures	Procedures (including surgery, imaging, and genetic testing) this patient has undergone, dated and linked to a cancer type if available
family_history	List of cancer conditions in the patient's family history, with specific listing of the relevant family member, if known

15 core tables, > 300 data elements and growing

Updated nightly





Data Element	Increase %
Histology	67.5
Stage	19.5
Metastasis	39.9
ER	34.9
PR	34.2
HER2	34.6
EGFR	47.1
ALK	106.9
BRAF	81.5
RET	29.6
ROS1	17.6

% increase in record count after incorporating NLP data





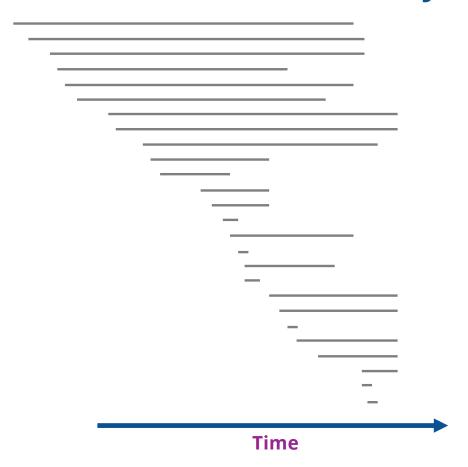
The Power of an Al-Augmented Data Model in the Real World

Who could benefit from a newly-approved ROS1-targeted therapy?





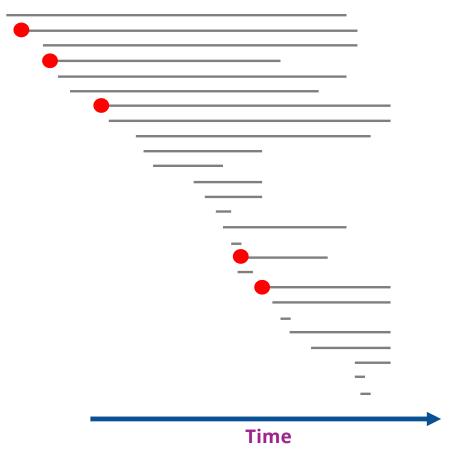
Patients with a ROS1 fusion by NGS







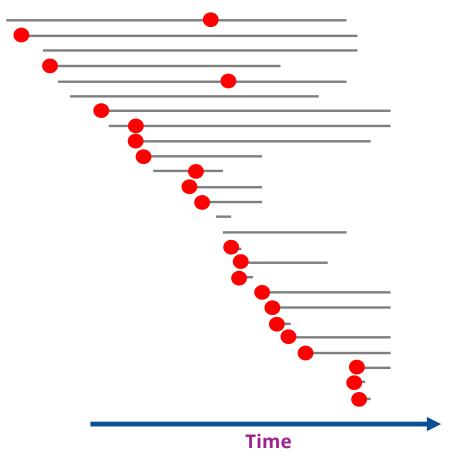
Captured by the EMR (n=5)







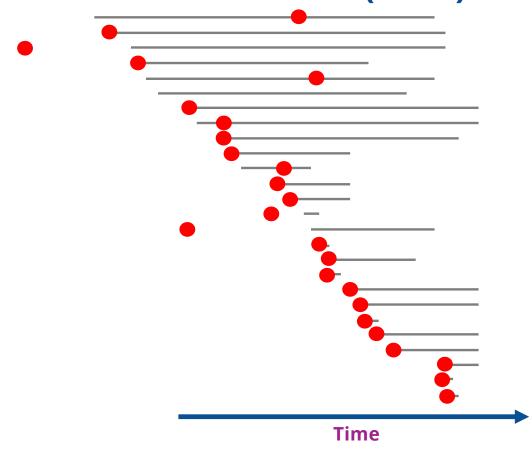
Captured by live data feed from NGS providers (n=22)







Recovered by NLP/LLM on clinic notes and scanned documents (n=26)





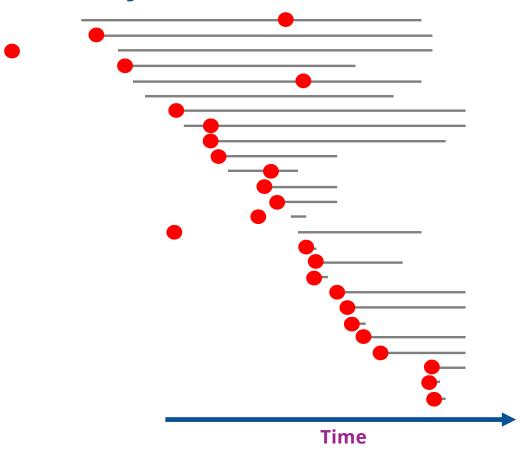


Key Finding 1: You'll underestimate the true patient population unless you take a multimodal approach





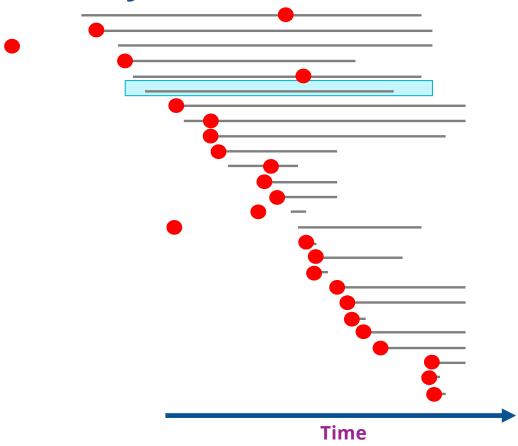
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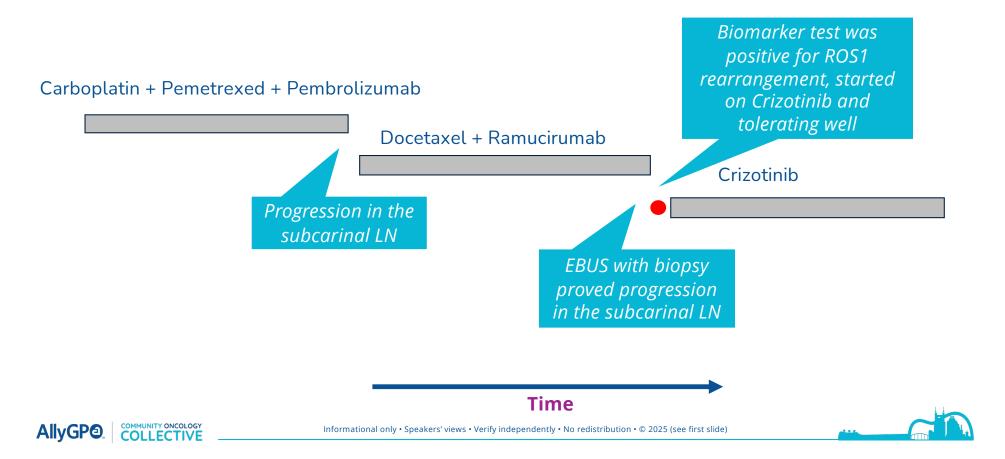
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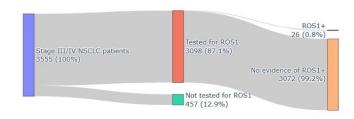






'Patient Journey' constructed from an Al reading of clinic notes

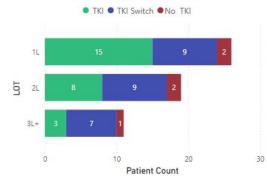




Was NGS testing optimal?

Key Finding 2: Comprehensive patient journeys allow us to dig deeper Distribution of Patients by LOT

Were treatments and treatment sequences optimal?







Would you have managed this patient differently?





What if an AI system suggested different management?





What is possible now

- Can fill in the blanks and correct errors in complex patient histories
- · Gain a better understanding of our patients at massive scale

Volume-based contracting

Abstraction-heavy Ol projects

Manual matching to trials

→ 'Clinically rational' contracting

Abstraction-heavy QI projects → Real-time dashboards

→ Automated and efficient matching













What will be possible soon

- Placing your patient on a pathway such as NCCN
- Data-driven recommendations for the next stage of their care

What will not be possible soon

Al making clinical decisions: It's an assistive technology

What can you do now?

- Assess your data infrastructure
- Understand your knowledge gaps and how accurate data might be applied
- Find a data partner who gives something back to you





QUESTIONS AND

COMMENTS





Thank You



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