

Event Flow: Event Feedback Analytics Dashboard

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Abstract: *The logistical and financial investments involved are enormous in order to coordinate programmatic events such as technical workshops and academic seminars. One-dimensional feedback systems that do not explain critical variables such as high attendee drop-off rates, statistical opinion bias, and the multidimensionality of human emotion as reflected in unstructured qualitative feedback are often relied upon to assess the programmatic success. Moreover, legacy analytics have high temporal latency and do not have what is referred to as Logic Integrity, that is, a numerical rating does not correspond to the written comment. EventFlow, a powerful data engineering pipeline and interactive business intelligence dashboard are introduced in this paper. The system, which is built using Python, Pandas, Firebase Firestore and Streamlit, processes unstructured feedback data in real-time. It uses the Natural Language Processing (NLP) deterministic, lexicon-based sentiment analysis model, VADER (Valence Aware Dictionary and sEntiment Reasoner). The analytical engine quantifies mathematically the two variables of the analysis, namely, the Experience Stability and the Opinion Bias. The first strategic product is an active event performance matrix, a direct conversion of the Boston Consulting Group (BCG) Growth-Share Matrix, making resources allocation, target marketing strategies, and a comprehensive involvement of the attendees possible.*

Keywords: Event Analytics, Sentiment Analysis, Natural Language Processing, VADER, Business Intelligence, Data Pipeline.

I. INTRODUCTION

The world events, conferences and experiential marketing industry is at a stage of radical change of technology and mode of operation. In the past, subjective methods like anecdotal responses and physical estimations of crowds were used in evaluating success. Nonetheless, contemporary functional ecosystems require unbiased, fact-based methods. A severe lack of connection is usually created between quantitative data structures and qualitative data streams. The participants often provide conflicting data because of survey fatigue giving high numerical rating and critical frustration in operations left to the open-ended comments or the other way around. This is an exit between quantitative contribution and qualitative reality, which is termed as a failure in Logic Integrity.

The failure of Logic Integrity renders relying on the arithmetic mean of the numerical ratings very inaccurate. In addition, there is a phenomenon of the so-called Critical Drop-off that bothers organizations: the quantitative difference between the top-of-funnel registration, and the actual, confirmed bottom-of-funnel attendance. Traditional analytical pipelines obscure these drop-offs by merely averaging the feedback of the real attendees and creating an illusion of crippling success and ignores the existence of huge financial and operational inefficiencies.

In order to fill these profound analytical lacuna, this study suggests EventFlow: an end-to-end Extract, Transform, Load (ETL) pipeline and real-time dashboard. The project removes building a data silo and time delay between events, which can be caused by manual and legacy post-event surveys. With the help of the advanced Natural Language Processing (NLP) and the powerful statistical modeling, EventFlow is able to convert the unstructured attendee sentiments to actionable and prescriptive business intelligence.



II. THEORETICAL FRAMEWORK AND METHODOLOGY

One simple method of coping with the modern institutional constraints is to model complex mathematical operations in the backgrounds through a highly responsive front end. EventFlow is based on a decoupled, serverless architecture consisting of a Python-based backend execution environment, Streamlit to render interactive user interfaces, and Firebase Firestore, a flexible, NoSQL data ingestion service, available on the Google Cloud Platform.

A. The VADER Lexicon Paradigm

EventFlow uses VADER, an open-source sentiment analysis tool based on a rule-based sentiment analysis system and using lexicon optimized to work with informal language, rather than using computationally expensive and opaque Deep Learning Large Language Models (LLMs). VADER has an optimal linear time algorithmic complexity of $O(N)$, and has no computational latency in real-time bulk ingestion. VADER computes the intensity of sentiment, using five generalized heuristic rules: Punctuation multipliers, Capitalization emphasis, Degree Modifiers (boosters and dampeners), Contrastive Conjunctions (polarity shifts), and Negation (N-Gram Polarity Reversal). The resultant "Compound Score" is mathematically scaled to a strict range between negative 1.0 (extreme negative) and positive 1.0 (extreme positive), mathematically transforming subjective text into quantitative and bounded operations.

TABLE 1 VADER METRIC INTERPRETATION AND NUMERICAL BOUNDS

VADER Metric	Numerical Bounds	Algorithm Description and Interpretation
Negative (neg)	0.0 to 1.0	The fractional proportion of the text string exhibiting explicitly negative emotional polarity.
Neutral (neu)	0.0 to 1.0	The fractional proportion of the text string lacking any distinct, identifiable emotional polarity.
Positive (pos)	0.0 to 1.0	The fractional proportion of the text string exhibiting explicitly positive emotional polarity.
Compound Score	-1.0 to +1.0	The fully normalized, one-dimensional, aggregated sentiment score of the entire string.

The resulting "Compound Score" is mathematically normalized to a strict range between -1.0 (extreme negative) and +1.0 (extreme positive), mathematically mapping subjective text into bounded quantitative operations.

B. Statistical Feature Engineering

To go beyond a piece of simple arithmetic averages, the system uses higher-order statistical moments to attendee feedback:

- Experience Stability (Standard Deviation): The system calculates the population Standard Deviation of numerical ratings to measure the consistency. Having a low standard deviation means that there is highly uniform execution and having a high standard deviation means that there is polarized delivery and operational risk.
- Opinion Bias (Skewness): the coefficient of Skewness of the feedback is used to mathematically map the directional asymmetry of the feedback. A negative skew means that those who were vocal minority had a bad experience that was carrying the average down and a positive skewness means generally poor execution that is being masked by a few positive outliers.

III. IMPLEMENTATION AND RESULTS

The system's operational capability is structured through a rigorous five-step automated processing and ETL pipeline.

A. Cloud Ingestion and Simulation

A high-fidelity Data Simulation Engine was developed using Python, the Faker and NumPy libraries. This engine purposefully injects statistical noise, duplicate records, null values and paradoxical sentiment structures (e.g., 5-star ratings with highly negative text) in order to rigorously stress-test the downstream data-cleaning policies.



B. Smart Data Cleaning and NLP Cleaning.

Data that is consumed on the Firestore cloud is deduplicated with a strict deduplication using a multi-column composite key. Explicit null-handling Mathematically excludes ratings of people labeled with false attendance. Then normalization of text is done using regular expressions (Regex) to strip non-alphanumeric punctuation and impose lowercase formatting, to prepare it to be processed by the NLP engine.

C. NLP Alignment and Checking of Logic.

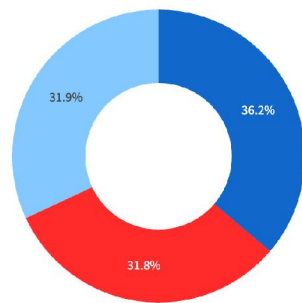
Computational checks of the system include the Logic Integrity, the scores of the VADER compound and the explicit numerical star rating are compared. In case of polarities (e.g., high rating with a positive text compound score), the data point is confirmed. The existence of contradictions will lead to a failure flag. In simulation testing, the VADER NLP engine was able to identify anomalies and compute a "Logic Match Rate" and avoided biased executive summaries that might have occurred as a result of user interface errors or survey survey rush submissions.

AI Mood Validation (Consistency Check)

How we validate the data: We use a Natural Language Processing (NLP) AI model called VADER to read the attendees' written comments. We then compare the "emotional mood" of their writing with the numerical "star rating" they clicked.

If the match rate is high, it proves that our feedback system is capturing genuine sentiment rather than random clicks or rushed form submissions.

Polarity Distribution



Logic Match Rate (%)

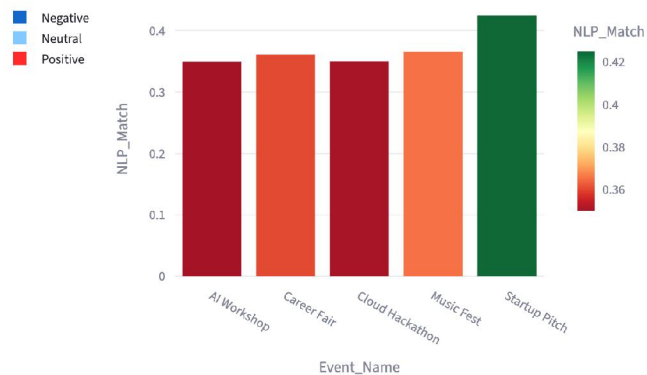


Fig. 1. AI Mood Validation dashboard demonstrating the logical consistency check between numerical ratings and textual sentiment.

During simulation testing, the VADER NLP engine successfully identified anomalies and calculated a "Logic Match Rate," successfully avoiding skewed executive summaries caused by user interface errors or rushed survey submissions.

D. Strategic Output

The pipeline aggregates granular user data into an interactive Plotly-based Event Performance Matrix. Events are classified into four strategic quadrants:

TABLE II EVENT PERFORMANCE ZONE QUADRANT CHARACTERISTICS AND STRATEGY

Event Performance Zone	Quadrant Characteristics (Metrics)	Strategic Implication and Action Plan
Stars (Bottom Left)	Low Drop-off Rate, High Satisfaction Rating	Highly engaging core organizational value. Actively scale and optimally



		fund.
Mass Outreach (Top Left)	Low Drop-off Rate, Low Satisfaction Rating	High attendance but poor qualitative experience. Requires immediate structural redesign.
Hidden Gems (Bottom Right)	High Drop-off Rate, High Satisfaction Rating	Excellent experience but poor marketing/scheduling. Pivot investment toward registration retention.
Risks (Top Right)	High Drop-off Rate, Low Satisfaction Rating	Significant abandonment and dissatisfaction. Systematically phase out.

Decision Support: Quadrant Logic

Investment vs. Satisfaction Matrix

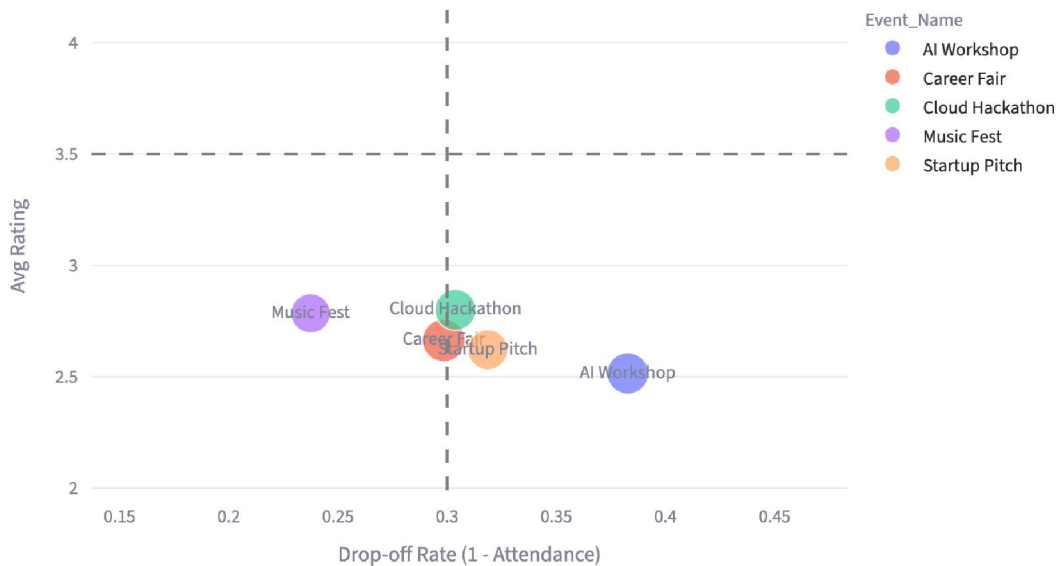


Fig. 2. The Event Performance Matrix visualizing Drop-off Rates versus Satisfaction Ratings for strategic decision support.



Statistical Signals & Correlation

Event Performance & Consistency

Event_Name	Average Rating	Consistency (StdDev)	Opinion Bias	Drop-off Risk
AI Workshop	2.51	1.25	0.31	0.38
Career Fair	2.66	1.27	0.22	0.3
Cloud Hackathon	2.8	1.26	-0.02	0.3
Music Fest	2.78	1.2	0.08	0.24
Startup Pitch	2.62	1.16	0.15	0.32

Consistency (Standard Deviation):

- **Low (Good):** Most attendees agreed on their rating. The experience was stable.
- **High (Warning):** Attendees had wildly different opinions. This suggests a "hit or miss" event.

Opinion Bias (Skewness):

- **Negative:** Most were happy, but a few very unhappy attendees pulled the average down.
- **Positive:** Most were unhappy, but a few "super fans" inflated the score.

Fig. 3. Dashboard view highlighting Experience Consistency (Standard Deviation) and Opinion Bias (Skewness).

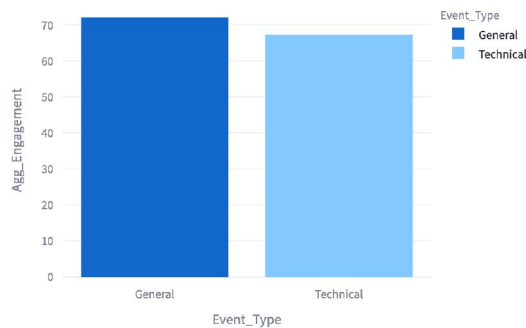
Moreover, segment analyses were effective in showing macroscopic trends of operation. By example, since organizers can group events together by type, they were able to objectively track that Technical workshops had higher drop-off rates than General networking events, giving them objective grounds to allocate their budget in the future.

Segment Analysis: Technical vs. General

This compares how we execute highly technical workshops versus general networking events, helping accurately allocate future budgets and resources.

Engagement per Category

Engagement % by Type



Sentiment per Category

Mood by Type

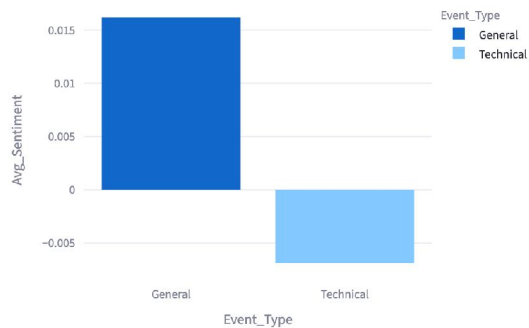


Fig. 4. Segment Analysis comparing engagement and sentiment between highly technical workshops and general networking events.



IV. CONCLUSION

The failure of most modern event management to achieve a critical business objective as a result of the failure to quantitatively measure qualitative human emotion on a large scale is addressed effectively by the EventFlow dashboard. The system avoids the structural limitations of traditional surveys and the computationally expensive LLMs, by integrating Streamlift and Firebase NoSQL databases, and exploiting the $O(N)$ linear time complexity of the VADER lexicon algorithm. The use of high-end statistical feature engineering, namely standard deviation to represent Experience Stability and skewness to represent Opinion Bias, the raw data is turned into strategic intelligence. The computation of these metrics in the adapted version of Event Performance Matrix, gives organizers the objective of allocating budgets and the effective redesign of operations. Future scope: Lightweight Aspect-Based Sentiment Analysis (ABSA) should be integrated into the project to provide detailed insight into attendees to prevent event execution and attainment of the ultimate objective, namely retention of attendees (Jones 1996).

V. ACKNOWLEDGMENT

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