Intellige: A User-Facing Model Explainer for Narrative Explanations

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Abstract
Predictive machine learning models often lack interpretability, resulting in low trust from model end users despite having high predictive performance. While many model interpretation approaches return top important features to help interpret model predictions, these top features may not be well-organized or intuitive to end users, which limits model adoption rates. In this paper, we propose Intellige, a user-facing model explainer that creates user-digestible interpretations and insights reflecting the rationale behind model predictions. Intellige builds an end-to-end pipeline from machine learning platforms to end user platforms, and provides users with an interface for implementing model interpretation approaches and for customizing narrative insights. Intellige is a platform consisting of four components: Model Importer, Model Interpreter, Narrative Generator, and Narrative Exporter. We describe these components, and then demonstrate the effectiveness of Intellige through use cases at LinkedIn. Quantitative performance analyses indicate that Intellige’s narrative insights lead to lifts in adoption rates of predictive model recommendations, as well as to increases in downstream key metrics such as revenue when compared to previous approaches, while qualitative analyses indicate positive feedback from end users.

Keywords: model interpretation, user-digestible narrative explanation, sales & marketing insights.
1. Introduction

Predictive machine learning models are widely used in a variety of areas in industry. For example, in sales and marketing, predictive models can help determine which potential customers are likely to purchase a product, and in healthcare, they can assist clinicians in detecting the risks of certain diseases. Complex predictive models such as random forest, gradient boosted trees, and deep neural networks can produce more accurate predictions than simple models such as linear regression and decision trees, and are therefore preferred in many use cases where prediction accuracy is of utmost importance. However, one important challenge is explaining model predictions to end users who are experts in their domains, using application-specific platforms and language. Previous literature points out that users can be reluctant to use the predictive models if they do not understand how and why these models make predictions [1], [2]. Therefore, building a user-facing model explainer that provides model interpretation and feature reasoning becomes crucial for engendering trust in prediction results and creating meaningful insights based on them.

Unfortunately, most complex predictive models with high predictive performance are intrinsically opaque, causing difficulties in intuitive interpretations. Even though some models output a list of globally important features to interpret the overall model prediction, usually no interpretations at individual sample level are produced. For example, in sales prediction, it may be that for customer A, browsing time is the most important feature whereas for customer B, discount is the most important. A sales team may strategize different customers individually by learning each customer’s own top features. Therefore, developing a user-facing model explainer which provides feature reasoning at individual sample level is of critical need [3].

There exist several state-of-the-art model interpretation approaches that enable sample-level feature reasoning, e.g., LIME [3], KernelSHAP [4], and TreeSHAP [5]. These approaches produce feature importance scores for each sample, indicating how much each feature has contributed to the model prediction. A typical example of model prediction and interpretation results using LIME for a jobs upsell model in LinkedIn sales prediction is shown in Table 1. Here, a random forest model predicts how likely each LinkedIn customer is to purchase more job slot products at contract renewal by using over 100 features covering areas such as job slots usage, job seeker activity, and company level attributes.

The left panel of Table 1 displays the model outputs with the interpretation results for a specific customer in jobs upsell prediction. Here, even though we have conducted sample-level feature reasoning by providing top important feature lists, there still exist several challenges when surfac-
Table 1. Model prediction & interpretation result (left panel) and narrative insights (right panel).

| Model Prediction & Interpretation (Non-Intuitive) | Narrative Insights (User-Friendly) |
|--------------------------------------------------|------------------------------------|
| Propensity score: 0.85 (Top 2%)                   | This account is extremely likely to upsell. Its upsell likelihood is larger than 98% of all accounts, which is driven by: |
| Top important features (with importance score):   | • Paid job posts changed from 10 to 15 (+50%) in the last month. |
| • paid_job_s4: 0.030                              | • Views per job changed from 200 to 300 (+50%) in the last month. |
| • job_view_s4: 0.013                              | • ... |
| • hire_cntr_s3: 0.011                             | • ... |
| • conn_cmp_s4: 0.009                              | • ... |

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| • job_view_s4: 0.013                              | • ... |
| • hire_cntr_s3: 0.011                             | • ... |
| • conn_cmp_s4: 0.009                              | • ... |

The rest of the paper is organized as follows. Section 2 lists related work in the area of model interpretation and narrative generation; Section 3 describes the design of Intellige; Section 4 presents use cases of Intellige at LinkedIn, including performance evaluation results; Section 5 points out some limitations of Intellige and discusses future directions; and Section 6 concludes our work.

2. Related Work

Model interpretation approaches that focus on sample-level feature reasoning have been widely explored in recent years. Examples include Shapley Value [7][8], Local Gradient [9], Integrated Gradient [10], Quantitative Input Influence (QII) [11], Leave-One-Covariate-Out (LOCO) [12], LIME [3], KernelSHAP [4], and TreeSHAP [5]. Moreover, many model interpretation platforms have also been developed to facilitate the implementation of these approaches in a unified way, e.g., Microsoft InterpretML [13] and Machine Learning Interpretability (MLI) in H2O Driverless AI [14]. All these model interpretation approaches and platforms can easily suffer from one challenge when interpretation results are presented to end users: feature importance scores in tabular/bar-chart format may not be very intuitive, resulting in low adoption rates.

To overcome this limitation, user-digestible narrative-based and template-based. Examples of neural network generation-based approaches include synthesizing explanations triggered by the word “because” [17][18], leveraging LSTM to generate explanation sentences [19], creating tips for Yelp restaurants based on GRU [20], and developing a multi-task recommendation model which performs rating prediction and recommendation explanation simultaneously [21]. However, generation-based approaches highly depend on the quality and quantity of training data, thus are less generalizable than template-based approaches.

Recent work on creating narrative explanations via template-based approaches includes imputing the predefined narrative templates with the most important features to explain the recommendation models [22][23][24]. In [25], a Java package provides narrative justifications for logistic/linear regression models. [26] propose a way to generate narrative explanations using logical knowledge translated from a decision tree model, and [27] introduce a rule-based explainer for a GDPR automated decision which applies to explainable models. However, all these aforementioned templated-based approaches are only applicable to a subset of machine learning models, and can easily fail when facing a more complex model such as a random forest. Moreover, the templates used in these approaches are predefined, with limited variations, and as a result, the generated narratives can become repetitive and hard to customize. In Intellige, we overcome these limitations by implementing model-agnostic interpretation approaches which apply to arbitrary predictive machine learning models, and by providing a user-friendly interface that allows customizing an unlimited number of narrative templates.

3. Intellige Design

3.1. Overview

We propose Intellige as a self-service platform for user-facing explanation. Intellige demystifies the outputs of pre-
dictive models by assigning feature importance scores, and converts non-intuitive model predictions and top important features into user-understandable narratives. This enables end users to obtain insights into model predictions, and to build trust in model recommendations.

Intellige is designed to support all the commonly-used black-box supervised machine learning models, including but not limited to support vector machines, bagging, random forests, gradient boosted trees, and deep neural networks.

Several challenges existed in the design and deployment of Intellige:

1. How to consume outputs from a range of machine learning platforms implementing machine learning models?
2. How to enable flexibility in choosing model interpretation approaches for different use cases?
3. How to efficiently generate template-based narratives while allowing narrative customization?
4. How to produce narratives compatible with a range of end user platforms?

To address the above challenges, we designed Intellige as a flexible platform consisting of four components: Model Importer, Model Interpreter, Narrative Generator and Narrative Exporter. These four components resolved the above challenges in sequential order. Figure 1 shows these four components:

1. **Model Importer**: Consumes model output from major machine learning platforms and transforms it into standardized machine learning model output.

2. **Model Interpreter**: Implements a collection of model interpretation approaches to process the standardized machine learning model output, and produces sample-level top important feature lists.

3. **Narrative Generator**: Creates user-digestible narratives via a template-based approach, based on the standardized machine learning model output, and additional feature information and narrative templates provided by Intellige users; selects top narratives by using top important feature list for each sample.

4. **Narrative Exporter**: Surfaces sample-level top narratives onto major end user platforms with necessary format adjustments.

In the following sections, we introduce these four components in more detail.

### 3.2. Model Importer

As we move toward machine learning platforms such as ProML from LinkedIn, AutoML from Google, and Create ML from Apple, it is very likely that different platforms produce model outputs in very different formats, resulting in low efficiency of developing model explainers specifically for each platform. A natural resolution is to first convert these model outputs into standardized format. This leads to the development of Model Importer.

The Model Importer takes the model output from a set of machine learning platforms as its input, and produces standardized machine learning model output, which will be used in the following Model Interpreter and Narrative Generator. For use cases at LinkedIn, the set of machine learning platforms includes ProML and other internal platforms built by data science teams. A typical standardized machine learning model output consists of feature vectors and prediction scores of all the samples, and optionally the predictive model itself with a unified interface (i.e., the interface should take standardized input (feature vectors) and produce standardized output (prediction scores)). We set the predictive model to be optional, since the following Model Interpreter can sometimes work well even without access to the original model, and the Narrative Generator does not depend on the original model.

### 3.3. Model Interpreter

Model Interpreter is the second component of Intellige, aiming to reveal insights behind machine learning model recommendations. It takes the output of Model Importer as its input, and produces sample-level top important feature lists by calculating feature importance scores for each sample, which are then conveyed to the Narrative Generator as one of its inputs.

The Model Interpreter consists of a collection of model interpretation approaches with a unified input format (i.e., standardized machine learning model output) and a unified output format (i.e., sample-level top important feature lists). The collection of model interpretation approaches includes state-of-the-art methods that produce sample-level feature importance scores, e.g., LIME [3], KernelSHAP & DeepSHAP [4], and TreeSHAP [5]. The Model Interpreter need not have the model itself accessible – the model may be trained in a separate system/device or there exist privacy/security concerns. If that is the case, high-performing model interpretation approaches, such as K-LIME, are available [14].

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1[https://engineering.linkedin.com/blog/2019/01/scaling-machine-learning-productivity-at-linkedin]
2[https://cloud.google.com/automl]
3[https://developer.apple.com/machine-learning/create-ml]
Intellige users have the flexibility to choose the appropriate interpretation approach in their use cases: For example, if the input machine learning platform implements a restricted set of machine learning algorithms (e.g., only tree-based algorithms or neural-network-based algorithms), then Intellige users can choose model-specific interpretation approaches such as TreeSHAP and DeepSHAP as they are usually more computationally-efficient than model-agnostic ones; On the contrary, if the original platform keeps a large set of candidate algorithms, then model-agnostic interpretation approaches such as LIME and KernelSHAP are recommended.

3.4. Narrative Generator

Narrative Generator is the key innovative part of Intellige, as it generates human-understandable narratives for interpreting model predictions. Its input consists of the outputs from Model Importer and Model Interpreter, as well as Insights Design, which in turn consists of a Feature Info File and Narrative Templates (shown in Figure 1, details provided in Section 3.4.1-3.4.4). The design of Narrative Generator is challenging: Information solely from the model itself such as feature name, feature value, and feature importance score may not be comprehensive enough for narrative construction. Additional information such as feature descriptions and narrative templates are needed as well.

To address the above challenge, we propose the Narrative Generator, with the goal of minimizing the human effort in narrative generation while keeping the flexibility in narrative customization. Many heavy tasks, such as feature value extraction, template imputation, and narrative ranking are handled inside the Narrative Generator in an automated way.

To enable narrative customization, we introduce Insights Design, an additional input to Narrative Generator provided by Intellige users. Insights Design contains information from domain knowledge owners which cannot be directly extracted from the model itself, but is essential to narrative construction. Insights Design has two components: Feature Info File and Narrative Templates. The Feature Info File contains additional information for each model feature, including feature hierarchy information, detailed feature descriptions, and narrative template imputation rules. The Narrative Templates file contains a collection of templates for imputing appropriate feature values.

In the following sections, we describe key features of Narrative Generator in detail.

3.4.1. Four-Layer Feature Hierarchy

An intuitive way to understand feature meaning and the intrinsic relationship between different features is to construct a hierarchical structure for these features. In Intellige, we propose a four-layer feature hierarchy, where the original features are set to be the first layer. This feature hierarchy is manually constructed with the help of model owners, and is specified by Feature Info File in Insights Design. In practice, feature correlation analysis can also help in finding the appropriate hierarchical structure by providing feature grouping information.

Table 2 shows a sample feature hierarchy for 8 selected features from the jobs upsell model introduced in Section 1. There are four hierarchical layers for features in Table 2:

- **Original-feature layer (1st layer):** This layer contains all the original features used in the model.
We note that when the Narrative Generator was initially designed, it only consumed the original-feature and the super-feature layers as its input, as these two layers seemed necessary and sufficient in narrative generation. However, as more and more requests for narrative deduplication and narrative concatenation came in from Intellige users, we decided to add the ultra-feature and the category layers, in order to realize these two additional functionalities. In practice, Intellige users can choose whether to specify the ultra-feature and category layers based on their own use cases. For example, specifying the ultra-feature layer is recommended if the generated narratives contain too much redundant information, and specifying the category layer is recommended if end users prefer reading paragraphs. If Intellige users find it unnecessary to specify either of these two layers, they can simply set them the same as the super-feature layer to reduce preparation effort.

### 3.4.2. Narrative Template Imputation

An important prerequisite for narrative construction is building the narrative templates in Insights Design. Narrative templates are manually constructed with the help of model owners, and then translated into appropriate code for imputing feature values in Narrative Generator. An example of how to translate narrative templates into code can be found in Section A.1 in the Appendix.

Table 3 shows sample narrative templates for the jobs upsell use case. Here, we refer to `value_change` as an “insight type”: Each super-feature corresponds to one insight type, which determines the specific narrative template to use. `prev_value` and `current_value` in the template `value_change` are “insight items”: each original-feature under one super-feature corresponds to one insight item, which determines the position to impute the original-feature value into the narrative template. For example, as shown in Table 4, the original-features `job_view_s3` and `job_view_s4` under the super-feature `views per job` correspond to insight items `prev_value` and `current_value` respectively, where `prev_value` and `current_value` can be identified as two positions in the template `value_change` in Table 3. `percent_change` is an example of an “extra insight item” whose value
may not be directly extracted from original-features but can be derived by extra calculations on the existing insight items. For example, here percent_change = (current_value-prev_value)/prev_value*100. We note that the appearance of the original-features within a given narrative is solely determined by the design of the narrative template, rather than the importance scores of the original-features – we discuss the usage of these importance scores in Section 3.4.3. We also mention that, by default, all the original-features under one super-feature will appear in its corresponding narrative.

The introduction of “insight type” and “insight item” enables the reusability of narrative templates. For example, both super-features views per job and applicants per job share the same insight type, and thus their narratives are constructed based on the same template. Moreover, “insight item” enables the construction of sample-specific narratives, as each sample has its own feature values to be imputed.

In addition to Narrative Templates, we are now able to specify the complete version of Feature Info File within Insights Design: The Feature Info File consists of all the columns in Table 2 and 4: Original-Feature, Super-Feature, Ultra-Feature, Category, Insight Type, and Insight Item, which contains essential feature information for narrative construction. Three additional columns: Insight Threshold, Insight Weight, and Source, can also be incorporated as optional columns to make the narrative generation process more customizable. The detailed introduction of these three columns can be found in Section A.2 in the Appendix.

3.4.3. Narrative Ranking

By introducing the feature info file and narrative templates, we are able to construct a collection of narratives for each sample. However, too many narratives may overwhelm end users, so instead we aim to present them with a few selected ones which show the strongest signals to support the model recommendations.

To select the most important narratives in a scalable way, we leverage the sample-level top important feature list created from Model Interpreter to rank all the narratives, and then present the end users with the top ones. To this end, we introduce the narrative importance score, which reflects how large the contribution of each narrative is to the model prediction. We set the score to be the maximum importance score among all the original-features under one super-feature sharing the overlapped information. We can set $K = 1$ to make the generated narratives most concise. One example of conducting narrative ranking and deduplication in jobs upsell use case can be found in Section A.3 in the Appendix (Table 8).

Finally, we point out that narrative ranking has inherited a good property from feature ranking in Model Interpreter: narrative ranking is sample-specific. A narrative with the same content, e.g., views per job, can be ranked as No. 1 for customer A but No. 5 for customer B, indicating its different contributions in supporting the recommendations for different customers.

3.4.4. Narrative Concatenation

Narrative concatenation is enabled by the category layer of the four-layer feature hierarchy, where relevant narratives under the same category can be concatenated as a paragraph rather than a bullet-point list. The major goal is to make the narratives better-organized so that the narratives focusing on different aspects of the sample will not be mixed. In Intellige, narrative concatenation is optional.

We conduct narrative concatenation by using conjunction phrases such as “and”, “moreover” and “what’s more”. For example, for narratives corresponding to super-features views per job and applicants per job, the paragraph after narrative concatenation is “Views per job changed ..., and applicants per job changed ...”. We also introduce paragraph importance score to rank these paragraphs. Similar to narrative importance score, the paragraph importance score is determined as the largest narrative importance score among all the narratives incorporated in the paragraph.

3.4.5. Narrative Generator Design

We now describe the design of Narrative Generator. Figure 2 shows the six major steps in Narrative Generator:

I Construct super-feature mapping based on feature info file and feature vectors: For each super-feature, this mapping records its corresponding original-feature ids (i.e., positions in feature vector), ultra-feature, category, insight type and insight items.

II Collect information of all super-features for each sample: For each super-feature in one sample, we extract its corresponding original-feature values from feature vectors according to super-feature mapping from Step I.

III Obtain top super-feature list for each sample: Based on sample-level top feature lists from Model Interpreter
Table 3. Narrative templates for interpreting jobs upsell model.

| Insight Type     | Narrative Template                                      |
|------------------|---------------------------------------------------------|
| quantity         | Purchased \{quantity_num\} \{super_name\} for \$\{total_price\}. |
| value_change     | \{super_name\} changed from \{prev_value\} to \{current_value\} \{(percent_change)\%\} in the last month. |

Table 4. Insight type and insight item for selected features from jobs upsell model.

| Original-Feature | Super-Feature   | Insight Type | Insight Item     |
|------------------|-----------------|--------------|------------------|
| job_qty          | job slots       | quantity     | quantity_num     |
| job_dprice_usd   | job slots       | quantity     | total_price      |
| job_view_s3      | views per job   | value_change | prev_value       |
| job_view_s4      | views per job   | value_change | current_value    |
| job_viewer_s3    | viewers per job | value_change | prev_value       |
| job_viewer_s4    | viewers per job | value_change | current_value    |
| job_applicant_s3| applicants per job | value_change | prev_value       |
| job_applicant_s4| applicants per job | value_change | current_value    |

and super-feature mapping from Step I, we rank each sample’s top super-features by calculating narrative importance scores, and then use ultra-features to conduct deduplication (Section 3.4.3).

IV Obtain information of top super-features for each sample: For each sample, we join the information of all super-features from Step II onto the top super-feature list from Step III.

V Construct top narratives for each sample: For each sample, we conduct narrative template imputation for each top super-feature (Section 3.4.2).

VI (Optional) Construct top paragraphs for each sample: For each sample, we conduct narrative concatenation according to category name (Section 3.4.4).

3.5. Narrative Exporter

The generation of user-digestible narratives may not be the last step of a user-facing model explainer, instead the narratives should be further surfaced to various end user platforms such as sales/marketing intelligence platforms, Tableau dashboards and emails. Our solution is to incorporate an extra step called Narrative Exporter after the Narrative Generator, to unify the narrative surfacing process. Specifically, Narrative Exporter takes top narratives from Narrative Generator as its input, and converts them into a few specific formats of choice, such as html or email format. This step completes the end-to-end pipeline from machine learning platforms to end user platforms in Intellige.

4. Use Cases at LinkedIn

LinkedIn leverages data to empower decision making in every area. One such area is sales, where data scientists built predictive machine learning models for account recommendation, covering the entire business landscape from customer acquisition to existing customer retention. Most of these predictive models are black-box models, making it challenging for data scientists to surface model outputs to sales teams in an intuitive way.

Furthermore, LinkedIn sales teams use multiple internal intelligence platforms. One typical platform, Merlin, aims to help sales representatives close deals faster by providing personalized and actionable sales recommendations/alerts. Before Intellige, all these sales recommendations were rule-based. A typical example of rule-based recommendations is based on exploratory data analysis: Recommend the jobs upsell opportunity if views per job increased more than 10%, or the number of job posts increased more than 20% in the past month. As we can see, these rule-based recommendations were neither very accurate as model predictions nor scalable in their generation process.

Intellige has assisted LinkedIn data scientists in converting machine intelligence from business predictive models into sales recommendations on platforms such as Merlin, where LinkedIn data scientists are typically both model owners and Intellige users, while sales teams are the end users applying Intellige’s narrative insights to their work. One typical example of Intellige-based sales recommendations on Merlin is with jobs upsell alerts. As introduced in Section 1, the jobs upsell model predicts how likely each account is to purchase more job slots.
Figure 3 shows how the jobs upsell alerts appear on Merlin. When a sales representative logs into Merlin, a list of account alerts including jobs upsell alerts are displayed on the Merlin homepage (Figure 3(a)). On the summary page of the account, we see a sentence describing its propensity score. To learn more about the underlying reasons behind its recommendation, sales representatives can click the “Job Slots Upsell” button which will direct them to the account status page with more account details (Figure 3(b)). In the Account Status section, top narrative insights are listed, e.g., both viewers per job and distinct countries that job posts seek talents from largely increased in the last month, which serve as strong signals of upsell propensity.

Besides Merlin, Intellige-based sales recommendations have also been surfaced onto other sales platforms for different audiences and use cases with the help of Narrative Exporter. By the end of 2020, six Intellige-based sales recommendations across four lines of LinkedIn business - Talent Solutions (LTS), Marketing Solutions (LMS), Sales Solutions (LSS) and Learning Solutions (LLS) have been on-boarded onto four internal sales intelligence platforms, which have been surfaced to more than five thousand sales representatives overseeing more than three million accounts.

4.1. Evaluation Results

To understand how helpful Intellige-based sales recommendations are to sales representatives, we turned to qualitative and quantitative evaluations of Intellige performance.

In our qualitative evaluation, we collected feedback from sales representatives via questionnaires, interviews, and other feedback channels. Similar approaches have been proposed in [15] and [27], where the authors argued that “subjective satisfaction is the only reasonable metrics to evaluate success in explanation”. We have conducted a survey within a small group of sales representatives on the helpfulness of Intellige-based sales recommendations (ratings from 1 - not helpful at all to 5 - couldn’t do my job without them). Ten responses have been received with average satisfaction rating of 3.5 (standard error 0.4). We have also collected positive feedback from a broader group of sales representatives, which we summarized into three main points (A collection of feedback in the original can be found in Section A.4 in the Appendix):

1. Top narrative insights are clear to understand and effectively help sales representatives build trust in the account recommendations. These narrative insights bring important metrics to their attention, and prompt them to work on accounts that they may have not considered otherwise.

2. Intellige-based sales recommendations serve as a comprehensive information center. Sales representatives appreciate that the top narrative insights are consolidated all in one place, to save their time of gathering information from different sources.

3. Intellige-based sales recommendations provide a directional guidance for next steps. The top narrative insights allow sales representatives to act strategically, e.g., prepare customer-specific conversations.

Another way to evaluate the performance of Intellige-based sales recommendations is via quantitative evaluation, which we conducted in two phases:
1. Phase I: Compare the adoption rate between Intellige-based recommendations and rule-based recommendations. Table 5 shows the interaction rates on all the Intellige-based and rule-based Merlin Alerts across sales representatives in LTS and LLS respectively in the same 3-month time period, where the interaction rate is defined as # clicks / # impressions. Intellige-based alerts have a significantly higher interaction rate than rule-based alerts, indicating that sales representatives are more engaged with Intellige-based alerts. We note that potential confounding factors in this comparison may exist, e.g., the novelty of new alerts may lead to increased interactions. To address this novelty effect, we started our measurements of # impressions and # clicks one month after the new alerts launch date, in the hope that most of the sales representatives have already been familiarized with them. We have also extended the time period of measurements to three months to further reduce this potential novelty effect.

2. Phase II: Identify the differences with/without Intellige-based recommendations via A/B testing. In the A/B testing design, for each sales representative, we randomly split his/her account book into treatment/control groups, and we show the Intellige-based recommendations to all the eligible accounts in the treatment group only. We then compare key metrics between the treatment and control groups, e.g., upsell rate and revenue for upsell recommendations (upsell rate = # successful upsell opportunities / # sales opportunities created), and churn rate and revenue lost for churn risk notifications. Table 6 shows the A/B testing results of jobs upsell alerts and recruiters upsell alerts after a 3-month testing period, where “recruiters” is another LinkedIn product. We observe boosts in both key metrics: upsell rate and average spend per account, indicating that the Intellige-based sales recommendations work effectively in driving the right sales decisions and bringing in revenue to the company. We note that the A/B testing period of recruiters upsell alerts was during the COVID-19 crisis, where severe hiring freezes likely negatively impacted the market of recruiters products [28], leading to lower than expected numbers of created opportunities and upsell opportunities in Table 6. As a result, the corresponding upsell rate lift of recruiters product is not statistically significant, and its average spend per account possesses a relatively large standard error.

4.2. Lessons from Deployment

We list key lessons we have learned from the deployment of Intellige at LinkedIn:

1. Initial feedback we received after the launch of our first-ever Intellige-based sales recommendations - jobs upsell alerts, was from sales representatives who found some narratives confusing. For example, one narrative was “Distinct countries of job posts changed value”, which was identified as a vague statement: Did this mean “distinct countries where job post viewers come from” or “distinct countries where job posts seek talents from”?

To resolve the above issue, we worked with data scientists who built sales predictive models to host multiple working sessions with sales representatives. During working sessions, we walked through the top narrative insights with sales representatives, asked them about meaningfulness of feature descriptions and whether more granular information was needed, and then revised the feature descriptions and narrative templates in Insights Design accordingly. For example, when we identified which description was correct for “distinct countries of job posts”, we updated the corresponding super-feature in Insights Design, which solved the above issue. Overall, we found it useful to iterate through several rounds of improvements and feedback from our end users.
Table 5. Interaction rate (# clicks / # impressions) of Merlin Alerts, Intellige-based vs rule-based (standard error in parenthesis).

| Alerts Type          | # impressions | # clicks | Interaction Rate (s.e.) |
|----------------------|---------------|----------|------------------------|
|                      | LLS           | LTS      |                        |
| Intellige-based Alerts | 694           | 41       | 5.9% (0.9%)            |
|                      | 7,188         | 167      | 2.3% (0.2%)            |
| Rule-based Alerts    | 1,031         | 25       | 2.4% (0.5%)            |
|                      | 5,445         | 91       | 1.7% (0.2%)            |

Interaction Rate Lift

|                      | Lift (%)     | Lift (p-value) |
|----------------------|--------------|----------------|
|                      | +141%        | <0.001***      |
|                      | +39%         | 0.012**        |

Table 6. A/B testing results of jobs upsell alerts and recruiters upsell alerts (upsell rate = # upsell opportunities / # opportunities created) (standard error in parenthesis).

| Alerts Type          | Treatment/Control | # Opportunities Created | # Upsell Opportunities | Upsell Rate (s.e.) | Avg Spend Per Account (s.e.) |
|----------------------|-------------------|-------------------------|------------------------|---------------------|----------------------------|
| Jobs Upsell Alerts   | With Alerts       | 1259                    | 214                    | 17.0% (1.1%)        | $65,733 ($4,703)            |
|                      | No Alerts         | 422                     | 59                     | 14.0% (1.7%)        | $32,626 ($4,500)            |
|                      | Lift (%)          | -                       | -                      | +21%                | +101%                      |
|                      | Lift (p-value)    | -                       | -                      | 0.084*              | 0.074*                     |
| Recruiters Upsell Alerts | With Alerts       | 115                     | 11                     | 9.6% (2.7%)         | $25,863 ($14,209)          |
|                      | No Alerts         | 118                     | 7                      | 5.9% (2.2%)         | $2,908 ($1,236)             |
|                      | Lift (%)          | -                       | -                      | +63%                | +789%                      |
|                      | Lift (p-value)    | -                       | -                      | 0.214               | 0.071*                     |

*significance codes: 0 ‘***’ 0.01 ‘**’ 0.05 ‘*’ 0.1 ‘ ’ 1
**treatment/control split: 70/30 in jobs upsell alerts, 50/50 in recruiters upsell alerts

5. Limitations and Future Work

Here, we list several limitations of Intellige and discuss future work:

- Intellige only supports supervised machine learning models whose input features are in tabular data format. Future work will aim to extend Intellige to support a broader range of supervised learning models such as image classification and natural language processing models, as well as other types of models including unsupervised learning, semi-supervised learning and time series models.

- The Insights Design input, including the feature info file and narrative templates, is mostly manually created. We plan to investigate ways to auto-generate parts of Insights Design to further reduce manual efforts from Intellige users.

- Translation of narrative templates into code is manually conducted. As future work, we will try to automate this process by identifying symbols and characters in narrative templates and converting them into appropriate code automatically.
6. Conclusion

In recent years, requests from end users of predictive models of understandable model outputs have become widespread, motivating the development of user-facing model explainers. In this paper, we proposed Intellige, a novel user-facing model interpretation and narrative generation tool, which produces user-digestible narrative insights and reveals the rationale behind predictive models. The evaluation results in LinkedIn’s use cases demonstrate that the narrative insights produced by Intellige boost the adoption rate of model recommendations and improve key metrics such as revenue.

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A. Appendix

A.1. Translate Narrative Templates into Code

We use the narrative template `value_change` as an example to show how we can translate it into Scala code. This example can be easily generalized to other narrative templates and programming languages. Just to recap, the narrative template `value_change` is: “{super_name} changed from {prev_value} to {current_value} ({percent_change}% in the last month”).

To calculate the extra insight item `percent_change`, we can first build a helper function `changePercent` in Scala:

```scala
1 def changePercent(current_value: Double, previous_value: Double): String = {
2   val change_percent = (current_value, previous_value) match {
3     case (0, 0) => 0.0
4     case (a, b) => (a / b - 1) * 100
5   }
6   change_percent match {
7     case x if x.isInfinity => " "
8     case x if x >= 0 => " (+" ++ change_percent ++ ")"
9     case _ => " (" ++ change_percent ++ " ")"
10   }
11}
```

This helper function is used to first calculate the percent change from `prev_value` to `current_value` as `change_percent`, and then convert `change_percent` into a more user-friendly format: Empty if `change_percent` is infinite (e.g., changed from 0 to 4), (+X%) if `change_percent` is positive (e.g., changed from 2 to 4 (+100%)), and (-X%) if `change_percent` is negative (e.g., changed from 4 to 2 (-50%)).

With the help of this helper function, we can then build the Scala function `valueChangeInsight` for the narrative template `value_change` which enables feature value imputation:

```scala
1 2 3 4 5 6 7 8 9 10 11 12 13 def valueChangeInsight(super_name: String, insight_item: Map[String, Double]): String = {
14   val change_percent_desc: String = changePercent(insight_item("prev_value"), insight_item("current_value"))
15   (super_name.capitalize ++ " changed from " ++ insight_item("prev_value") ++ " to " ++ insight_item("current_value")) ++ change_percent_desc ++ " in the last month."
16}
```

This Scala function has two inputs:

1. `super_name`: The name of super-feature. E.g., views per job.
2. `insight_item`: A Scala Map which maps all the insight items in the narrative template to their corresponding feature values for each sample. E.g., for customer A, `insight_item = Map("prev_value" -> 100, "current_value" -> 150).

In practice, we can conduct narrative template imputation by simply calling this Scala function. For example, we can run the following Scala code if we want to construct narrative insight of super-feature `views per job` for customer A:

```scala
1 2 val narrativeInsightA = valueChangeInsight("views per job", Map("prev_value" -> 100, "current_value" -> 150))
```

The output will be “Views per job changed from 100 to 150 (+50%) in the last month”.

A.2. Additional Columns in Feature Info File

We briefly introduce three additional columns Insight Threshold, Insight Weight and Source in Feature Info File. A sample Feature Info File for the jobs upsell use case with these three columns included is shown in Table 7 (Due to space limitations, we omit columns that already exist in Table 2 and 4). Intellige users can work with model owners to fill in these three columns, and adjust their values based on feedback collected from end users:

```
| Original Feature | ··· | Insight Threshold | Insight Weight | Source |
|------------------|-----|------------------|----------------|--------|
| job_qty          | ··· | 0.8              | 0.8            | model  |
| job_dprice_usd   | ··· | 0.8              | user           |        |
| job_view_s3      | ··· | percent_change>10| 1              | model  |
| job_view_s4      | ··· | percent_change>10| 1              | model  |
| job_viewer_s3    | ··· | percent_change>10| 1              | model  |
| job_viewer_s4    | ··· | percent_change>10| 1              | model  |
| job_applicant_s3 | ··· | percent_change>5 | 1              | model  |
| job_applicant_s4 | ··· | percent_change>5 | 1              | model  |
```

- **Insight threshold**: This threshold can be used to filter out those narratives not meeting certain
criteria, so that the remaining narratives can be more relevant to end users. For example, the insight threshold for super-feature views per job is percent_change>10, thus only the narratives with the increment of job views larger than 10(%) will be shown to end users.

• **Insight weight**: This weight can be used to make adjustments to the narrative ranking. It takes values between 0 and 1 (default is 1), and is multiplied with the feature importance score from Model Interpreter to determine the final importance score for each original-feature. The motivation is to incorporate domain knowledge into narrative ranking: If we believe some original-features are predictive in modeling but not that informative to end users, we can lower their insight weights to prevent prioritizing their corresponding narratives.

• **Source**: Sometimes additional features from external data sources can also be used in narrative construction (together with model features). These additional features are usually in the formats incompatible with the predictive models (e.g., name, date and url), however, they can help make the generated narratives more informative. For example, a narrative can be “This customer spent 15 hours browsing websites last week, with the most visited website xyz.com”, where 15 is a model feature, and xyz.com is an additional feature which can not be fed into the model directly. We can set “source” to be model or user to specify the source of each original-feature. Note that one narrative cannot be constructed by using only the additional features, i.e., the additional features must be paired with at least one model features under the same super-feature, to make sure that a valid narrative importance score can be assigned for narrative ranking.

### A.3. Narrative Ranking Example

Table 8 shows one example of conducting narrative ranking and deduplication in jobs upsell use case for customer A. We set $K = 1$ in narrative deduplication.

**Table 8. Example of narrative ranking and deduplication in jobs upsell use case.**

| Original-Feature | Super-Feature | Ultra-Feature | Feature Imp. Score |
|------------------|---------------|---------------|--------------------|
| job_qty          | job slots     | job slots     | 0.3                |
| job_dprice_usd   | job slots     | job slots     | 0.4                |
| job_view_s3      | views per job | job view      | 0.2                |
| job_view_s4      | views per job | job view      | 0.6                |
| job_viewer_s3    | viewers per job | job view | 0.3                |
| job_viewer_s4    | viewers per job | job view | 0.2                |

⇓ **Narrative Importance Score Calculation**

| Super-Feature | Ultra-Feature | Narrative | Narrative Imp. Score |
|---------------|---------------|-----------|----------------------|
| job slots     | job slots     | Purchased 30 job slots ... | 0.4 |
| views per job | job view      | Views per job changed ... | 0.6 |
| viewers per job | job view | Viewers per job changed ... | 0.3 |

⇓ **Narrative Deduplication**

| Top Ultra-Feature | Top Narrative | Narrative Imp. Score |
|-------------------|---------------|----------------------|
| job view          | Views per job changed ... | 0.6 |
| job slots         | Purchased 30 job slots ... | 0.4 |

### A.4. Feedback from Sales Representatives

We list several comments from sales representatives in their original words:

- “These are awesome. I LOVE that you’ve called out the % of employees. All of these are SUPER helpful. The top insights are clear and concise. It would have taken me a lot of time to find all of that information, so I love that it is all laid out. It also prompts me to think more strategically, which I love.”

- “Most accounts were on my radar, but perhaps not for the reasons highlighted in the insights—so calling that out provides a new perspective on potential entry point into an account/ways to actively engage with relevant insight/reason.”
• “This SAR is clear to understand and is valuable by bringing important metrics to my attention. As I dig into SARs a bit more, time will tell which insights are most valuable to me.”

• “As someone new to LI, this is incredibly helpful. It points me into the right direction and allows me to take action quickly and in a way that correlates to an activity we are seeing in Sales Navigator.”

• “I love that the insights are consolidated all in one place, versus needing to run different reports in Merlin to gather the same information. I love the piece that highlights how many days reps are logging onto LinkedIn and searching on the platform.”

• “Yes it’s very valuable and useful for conversations. It helps with next steps and the insights will help it lots of different ways to tell a story to a customer depending on where that conversation is at or to help prospect in.”