INSIGHT-DRIVEN BUSINESS RULES FOR OPERATIONAL KNOWLEDGE

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ABSTRACT

Business process intelligence improves operational efficiency that is essential for achieving business objectives, besides facilitating competitive advantage. As organizations operate through inter-connected business processes, insights into their process performance through related business rules are essential to achieve business objectives. This paper outlines an approach for developing insight-driven business rules using the concept of buckets, which can lead to the development of a repository of business knowledge for business process operations. The proposed concepts are demonstrated through a prototype modeled on a hypothetical customer mortgage lending process, implemented using Oracle's PL/SQL database language.

KEYWORDS

Business Intelligence, Process Intelligence, Business Process, Business Rules, Oracle, PL/SQL

1. INTRODUCTION

Business rules are guidelines on how business activities are performed. Structurally such rules can be mere facts like "product X can only be purchased by business customers" or they may have a more complex structure whereby multiple facts collectively define some outcome in the form of IF fact (condition) THEN action (outcome). In such complex structures, a condition or a fact can be some assertion, while the action clause reflects the cumulative outcome of conditions or facts. Even though business rules are primarily associated with business operations, they are also a form of business operational knowledge that reflects on how the business operates.

Now as business intelligence (BI) techniques have transformed data into information and generated insights on an organization's business operations and competitive environment [10, 11, 12, 20, 22, 27, 28, 32, 33, 36, 38], it can also influence the nature and relevancy of business rules. Even though the utilization of such concepts to enhance business process insights through operational intelligence are evolving [5, 15, 16, 19, 21, 23, 26, 27, 28, 30, 31, 35, 36, 39], incorporating insights via business rules is limited. As organizations operate through inter-connected business processes, insights into their process performance through related business rules are essential to achieve business objectives, besides facilitating competitive advantage.

The traditional approach in business intelligence is to first model the data in a data warehouse in the form of multi-dimensional models through an analysis of business operations involving business process activities [34]. Thereafter, BI generates insights through online analytical processing (OLAP) in the form of star schema or its variants [1, 24, 25, 29, 40, 45]. Such analytics provide information on what combination of dimension factors (dimension attributes) are associated with various fact measure values or its aggregations. Even though OLAP analytics are important as it allows an organization to make sense of data by providing insights into

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business process operations, such insights can also be utilized to develop insight-driven operational business rules. Insight-driven operational business rules can allow a business process as well as an organization to be more responsive to the competitive environment. Below are examples of insight-driven operational business rules (BR) pertaining to an apartment complex:

BR-1:
IF customer credit score is high THEN allow apartment rental.
BR-2:
IF customer is W-2 employment THEN allow apartment rental.
BR-3:
IF customer is self-employed AND
Credit score is low
THEN decline apartment rental.

In the above business rules, the conditions are dimension attribute values while the action clause reflects the insight from OLAP analytics. Business insights can reflect some facts individually based on the analysis like BR-1 and BR-2 or facts could be grouped and expressed in a more complex business rules (BR-3).

While BI-generated insights are typically aggregated, an alternative approach could be to categorize them into distinct buckets. Each bucket groups insights based on criteria tied to their relevance to business processes and their alignment with success metrics. Such relevancy can range from insights that are making the business process more successful in contrast to insights that are not delivering success. After the buckets are created, each bucket can be analyzed independently for deeper insights.

Modeling of dimensional information via dimension attributes with business process activities is important for associating insight-driven business rules with relevant business process activity. Such association facilitates closer mapping of analytics and its insights to business process performance. An approach to model the flow of dimensional information with business process activities is referred to in the paper as dimensional flow model.

There have been attempts at operational intelligence in the form of process monitoring, process analysis, process discovery, conformance checking, prediction and optimizations [9, 17, 22]. Besides, utilization of business rules for business process intelligence has also been explored [4, 13, 21, 32]. However, these approaches either tie business rules to measures that are defined a priori through existing policies without much emphasis on database-driven business insights or express specific performance metrics through business rules concepts.

This paper aims to present an approach for developing insight-driven business rules that can be leveraged as actionable operational knowledge for optimizing business process operations. The paper in nutshell (i) outlines the dimensional flow model that associates relevant dimensional information with business process activities, (ii) develops a star schema for business process performance insights that are transformed into operational business rules, and then (iii) express insight-driven business rules for business processes activity through the concept of buckets. The paper illustrates the concepts through a prototype based on a hypothetical customer mortgage lending business process that is implemented in Oracle's PL/SQL database language.

The paper is organized in the following way. First the relevant operational intelligence research is reviewed. Next, the dimensional flow modeling concepts and the methodology to transform star schema into insight-driven operational business rules is outlined. The prototype application is illustrated next that shows the development of insight-driven operational business rules that can serve as business knowledge. The paper concludes by outlining how such insight-driven business rules can impact business process operations.

2. Related Work

Operational intelligence analyses business processes to ensure that the operational workflow is efficient and consistent with their business objectives. The goal is to optimize such processes for successful performance. There have been four approaches towards the utilization of BI concepts for business process based operational analytics. The first approach occurs in three variations in the form of (i) using BI concepts for dynamic process performance evaluation [8, 21, 23, 37, 41, 42, 44], (ii) analyze event logs to improve the quality of business processes [2, 3, 14], and (iii) monitor process instances to inform users about unusual or undesired situations [17]. These variations are either short on implementation or apply BI analytics to individual business processes for discrete performance assessment associated with business process activities; but there is no emphasis on how to enhance or incorporate insight-driven business rules into operational knowledge.

The second approach emphasizes analytics on selected business process activities within the modeling process [7]. It shows reference to analytic information during business process modeling as a way to incorporate BI. The approach emphasizes use case scenarios but is short on implementation details on how to evaluate performance.

The third approach focuses on utilizing BI to reduce redundant specifications of recurrent business functions when modeling business processes [43]. It fosters reuse of business function specifications and helps to improve the quality and comparability of business process models. This approach is focused on the modeling for individual business process only.

The fourth approach [18] outlines a framework to reengineer business processes structure through data analytics on external data. The approach lacks implementation details.

3. Dimensional Flow Model

Dimension flow model [22] is a graphical conceptual method to identify dimensional (analytic) information that can be considered as relevant for analyzing business process activities. Dimension flow modeling is based on information flow modeling concepts [21, 29] and is valuable because it provides a basis for separating information from transactional processing for analytical processing. Development of dimension flow can be beneficial for (i) understanding the nature of analytic information without the complexities of data storage, and (ii) comprehending how business process activities are affected by such information. Figure 1 shows the generic outline of a dimension flow model.

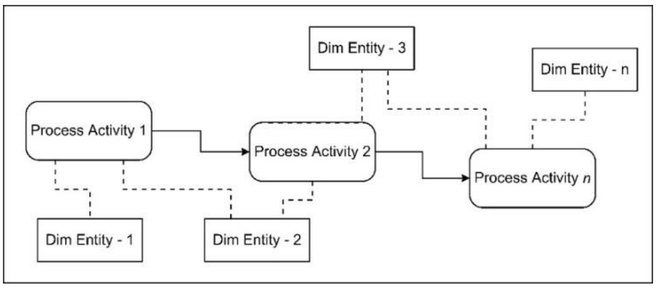

Figure 1. Dimension Flow Model

In Figure 1, the business process model consists of various activities labeled as Process Activity 1, Process Activity 2, and so on. Each process activity's utilization of dimensional information is represented through various dimensional entity types like Dim Entity - 1, Dim Entity - 2, and so on. It is possible that the same dimensional entity type may be utilized by other process activities, like Dim Entity - 2 interacts with Process Activity 1 and Process Activity 2, while Dim Entity - 3 interacts with Process Activity - 2 and Process Activity - n.

The dimensional entity types of the dimension flow model are derived from the transactional entity relationship model (ERD) of the business process. Each dimensional entity type structure may include some or all the attributes of the associated transactional entity type that are essential for the purpose of analysis. Unlike a transactional ERD data model, the dimensional entity types are standalone entity types which are considered as dimensions in associated multi-dimensional models.

Figure 2 shows an example of a dimensional flow model for a simplified mortgage lending business process. It can be categorized into four stages: (i) get pre-approval, (ii) get mortgage, (iii) loan processing, and (iv) close mortgage.

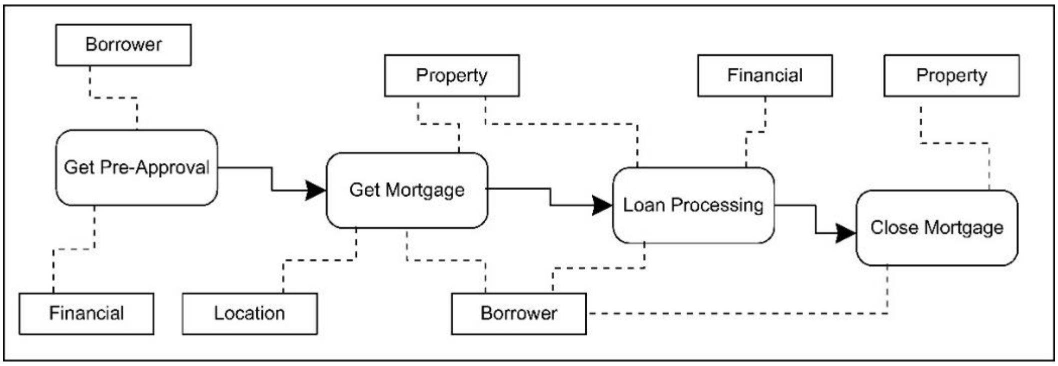

Figure 2. Mortgage Lending Dimension Flow Model

Get Pre-Approval is the initial activity that commences when a borrower approaches the mortgage company to get a pre-approval for buying a property. The Get Mortgage activity commences when the borrower has made an offer for a property and now wishes to take a mortgage on the property. As a mortgage involves taking a loan, the processing of the loan is performed by the Loan Processing activity. Once the loan is processed and approved, the sale of the property is finalized through the Close Mortgage activity.

At the surface level the dimension flow model may seem similar to data flow models [38]. However, the dimension flow model avoids some of the key tenets of the data flow models like decomposition, leveling, and data stores. It is derived from the operational data model wherein (i) the database relationships are ignored, and (ii) the entity types and attributes that should be part of analysis are selected. Figure 3 is the operational data model of Mortgage Lending.

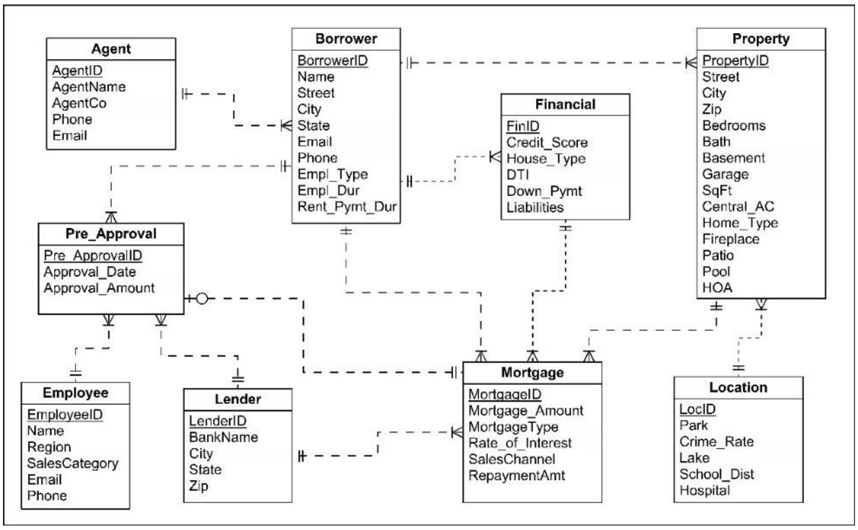

Figure 3. Operational Data Model for Mortgage Lending

The details of dimensions for mortgage lending multi-dimensional model (as derived from its operational data model shown in Figure 3) are shown in Figure 4. For instance, in the operational data model of Mortgage Lending there are many attributes in the Borrower entity type. But the Borrower dimension in Figure 4 only considered a few of the attributes. Similar considerations influence the selection of other dimension attributes.

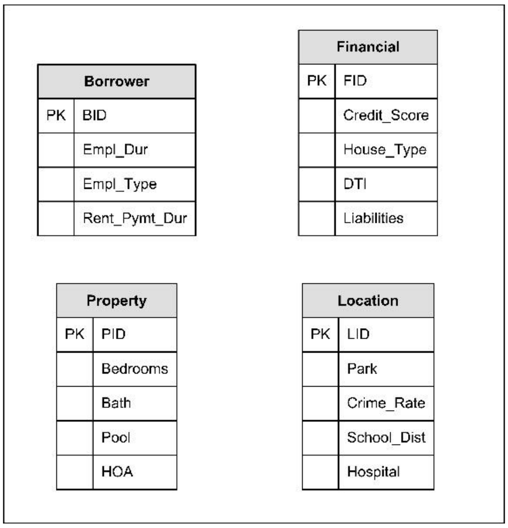

Figure 4. Mortgage Lending Dimension Flow Model Entity Types

The interaction of dimensional entity types in dimension flow model with business process activities enables a more accurate mapping of dimensional attributes with business process activities. Such mapping later facilitates the application of insight-driven business knowledge.

4. GENERATE INSIGHT-DRIVEN OPERATIONAL BUSINESS KNOWLEDGE

To generate insight-driven operational business knowledge an Oracle based prototype is developed wherein the dimension flow model is utilized to develop a star schema so that the schema reflects the business process more accurately. Thereafter the star schema is analyzed through buckets to discern the extent to which some or all of the dimensional entity type attributes provide any insight that can facilitate the development of business knowledge. In short, the steps involved in the development of insight-driven business operational knowledge are as follows: (i) create a star schema with some performance measure that is considered key to business process success, (ii) transform star schema analytics into analytic rules buckets, (iii) transform the analytic rules bucket insights into operational guidelines or knowledge and (iv) reference the dimension flow model to align insights with business process activity and incorporate insights with existing operational business rules.

The prototype is based on a hypothetical mortgage lending company. The proposed prototype as shown in Figure 5 consists of four dimensions and the performance measure in the fact table is the number of mortgages sold (NumSold attribute).

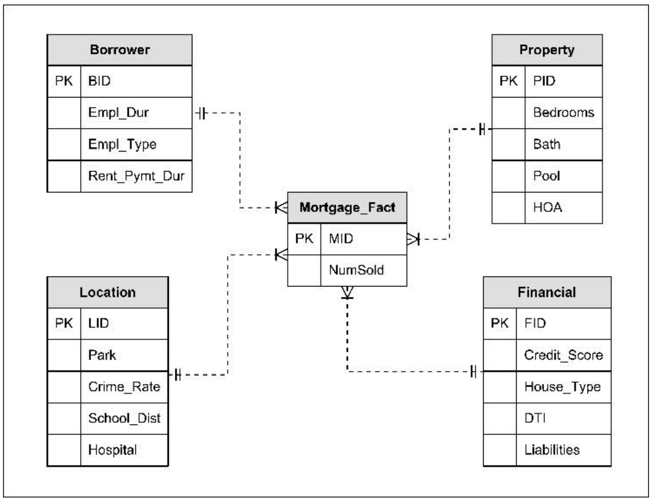

Figure 5: Mortgage Lending Multi-Dimensional Model

Suppose one criteria to determine the mortgage lending process performance is to know how many mortgages were sold successfully. The fact attribute that can provide this information is “NumSold” in the Mortgage_Fact table. In general, it is up to the business to decide what should be the appropriate attribute to measure business process success. Borrower, Location, Financial and Property are the dimensions. The dimension structure is not hierarchical. For the purpose of the prototype only certain attributes are considered for dimensions. A sample of the table structure of the above dimensions and success (fact) measures are listed in Appendix-A.

The approach for developing insight-driven business knowledge (as shown in Figure 6) involves many modules. The approach first determines the impact of each dimension with respect to the performance measure in the Business Process Analytics module and then it separates the analytics outcomes in buckets of High and Low in the Analytics Rules Bucket Base module.

Separating analytics outcomes into buckets provides a way to compartmentalize outcomes for further focused analysis in the Bucket Analysis module like determing some associations, patterns, trends, and so on. Such separation also allows determination of analytic outcomes that are supposedly working best in comparision to analytic outcomes that are not delivering the desired results. For example, if a dimensional attribute appears in all the buckets it may mean that the attribute is not critical or sort of default for business performance. A business can categorize its insights into multiple buckets based on relevancy. Reason for having two buckets in the prototype in the form of High and Low is to show (a) the feasibility of the concept with respect to generating insights, and (b) demonstrate the integration of insights into actionable business knowledge for business process operations.

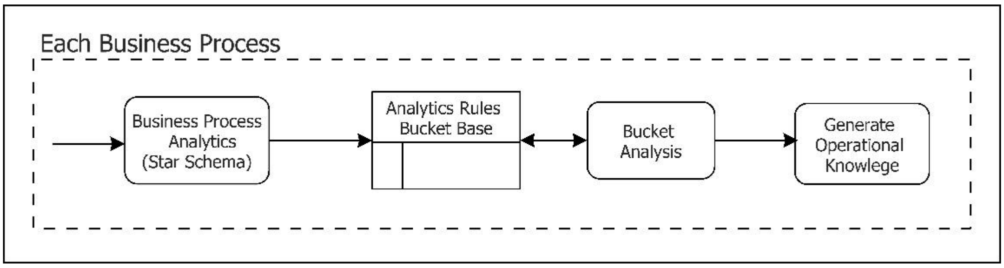

Figure 6 Insight-driven Business Knowledge Approach

High bucket is a collection of analytics outcomes that are associated with higher performance level. In the prototype it is set to 80% or more of mortgages sold. The Low bucket is a collection of analytics outcomes that are associated with lower performance level. In the prototype it is set to less than 50% mortgages sold. Once the initial analytic results are stored in each dimensional bucket, then such buckets are analyzed individually for detecting associations in each bucket. Such associations among each dimension attribute can then be grouped or individually framed as insight-driven business rules in Generate Operational Knowledge module.

4.1. Prototype

Logic of the prototype is shown in Figure 7.

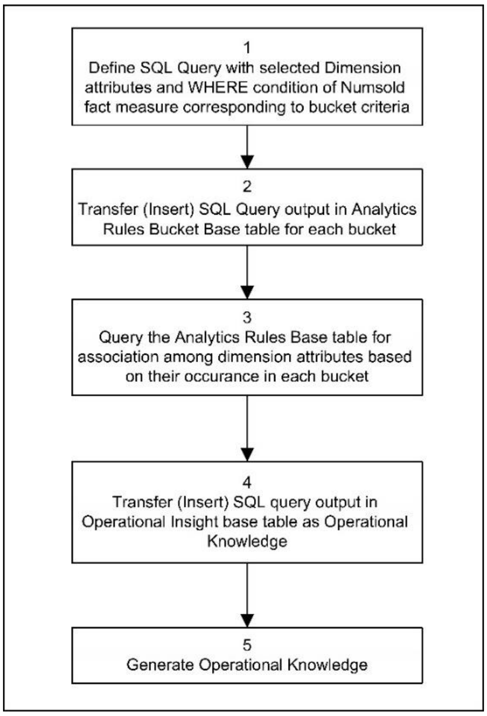

Figure 7 Insight-driven Business Knowledge Logic

4.1.1. Business Process Analytics Module (Logic Step 1 and Step 2)

A PL/SQL procedure containing queries will initiate the initial star schema analytics within the Business Process Analytics module and then populate the Analytic Rules Bucket Base. Below is a sample SQL query for selecting borrowers who have mortgages sold 80% of higher for High bucket (where t80 in the query is the value for 80% of the highest numsold value). Similar queries are utilized for Low bucket with different percentage. The adjoining pseudocode (Table 1) explains the logic.

Table 1	
<u>SQL Query</u> select borrower.bid, empl_dur, empl_type, rent_pymt_dur, count(*) as ctr from borrower,mortgage_fact,financial, location,property where borrower.bid = mortgage_fact.bid and financial.fid = mortgage_fact.fid and location.lid = mortgage_fact.lid and property.pid = mortgage_fact.pid and numsold >= t80 group by borrower.bid, empl_dur, empl_type, rent_pymt_dur having count(*) > 1;	<u>Pseudocode (for each bucket of a dimension)</u> For each dimension table frame a query - Select dimension attributes with count of output rows through inner join of all star schema tables where the fact table measure (numsold) value is within the bucket range and count of query output rows > 1 Process the query via PL/SQL cursor

The output of the queries pertaining to each of the buckets is transferred (stored) in a separate table (Table 1) for each dimension in the Analytics Rules Bucket Base module. Each table has the following structure:

Table 2							
ar_id	meas1	stat1	attr1_name	attr1_value	attr2_name	attr2_value	…

In Table 2, ar_id is the primary key, meas1 is the bucket threshold (fact) measure value, stat1 is the bucket label (like High or Low), attr1_name is dimension attribute1 name, attr1_value is dimension attribute1 value, attr2_name is dimension attribute2 name, attr2_value is dimension attribute2 value, and so on.

Following is the portion of PL/SQL source for transferring of the data from the star schema analytics query into the table ar_base_borrrower (structure shown in Table 2) for the borrower dimension. Similar source is utilized for the other bucket. The adjoining pseudocode (Table 3) explains the logic.

Table 3	
<u>PL/SQL cursor processing</u> for t80_cur_row in t80_cur loop insert into ar_base_borrower (ar_id,meas1,stat1,attr1_name,attr1_value, attr2_name,attr2_value, attr3_name,attr3_value) values (ar_base_bor_seq.nextval,t80,'High','Empl Dur',t80_cur_row.empl_dur,'Empl Type',t80_cur_row.empl_type,'Rent Pymt Dur',t80_cur_row.rent_pymt_dur); end loop;	<u>Pseudocode (for each bucket dimension)</u> Load Cursor: Query for each bucket For each cursor row output: - Insert table attribute name, table attribute value (query attribute value) Into bucket dimension table (Table 2) with bucket type (High or Low) and bucket threshold value.

4.1.2. Bucket Analysis Module (Logic step 3 and step 4)

Bucket analysis module will have separate database procedures for each dimension. It will count the number of times each dimension attribute value has appeared within each bucket. The attribute value that appears the most is then transferred to another table with the status ‘High’ or ‘Low’. Following is the SQL query to select borrowers with status ‘High’. Similar queries are utilized for other attributes in the dimension and thereafter for each bucket. The adjoining pseudocode (Table 4) explains the logic.

Table 4	
<u>SQL Query</u> select attr1_name, attr1_value, count(*) as ictr from ar_base_borrower where stat1 = 'High' group by attr1_name, attr1_value;	<u>Pseudocode (for each bucket dimension attribute)</u> For each dimension bucket table (Table 1) frame a query - Select dimension attribute name, dimension attribute value with count of output rows From dimension bucket table (Table 1) where bucket type (High or Low) Process the query via PL/SQL cursor

Each dimension bucket analysis outcome is transferred (stored) to a separate table (Table 5) that has the following structure:

Table 5				
bb1_id	attr1_name	attr1_value	level_state	lop

In Table 5, bb1_id is the primary key. Attr1_name is dimension attribute1 name, attr1_value is dimension attribute1 value. Level_state attribute is bucket level and lop attribute stores the logical operator value.

The following portion of PL/SQL source is utilized for transferring the data from the query from Analytics Rules Bucket Base into table borrower_buck1 (structure shown in Table 5) for the borrower dimension. Similar source is utilized for other bucket for each dimension. The adjoining pseudocode (Table 6) explains the logic.

Table 6	

<u>PL/SQL cursor processing</u>
open cur1;
hctr := 0;
loop
fetch cur1 into cur1_row;
exit when cur1%notfound;
if hctr <= cur1_row.ictr then
insert into borrower_buck1
values
(borrower_buck1_seq.nextval,cur1_row.attr1_name, cur1_row.attr1_value, 'High');
hctr := cur1_row.ictr;
end if;
end loop;
close cur1;
	<u>Pseudocode (for each bucket dimension)</u>
	Load Cursor: Query for each dimension bucket table (Table 2)
	For each cursor row output:
	Insert table dimension attribute name, dimension attribute value
	Into
	bucket analysis table (Table 5) with bucket type (High or Low)
	
	where the dimension attribute has the highest count in the bucket (High or Low).

4.1.3. Generate Operational Knowledge Module (Logic step 5)

The prototype associates attribute name with values that connote business sense like “Empl Dur less than 2 years” implies “Employment Duration less than 2 years”. It will generate business knowledge for each bucket thereby allowing the organization to determine how to take advantage of the insight. So, there would be (i) knowledge from the analytics for each dimension and then (ii) a collective knowledge for the entire business process with respect to each bucket.

The prototype will look for associations among the buckets with respect to dimension attribute values and develop various levels of operational knowledge. In this paper as mentioned before we focus on higher occurrences of dimension attribute values for each dimension in various buckets. Such business knowledge allows the organization to know which dimension attribute bring more revenue (or in case of mortgage lending more mortgages).

Providing knowledge for each dimension separately allows the organization to better utilize it with the individual business process activity associated with the dimension. Such knowledge from the analytics will change as more operational or external data is added with the passage of time allowing the organization to become more flexible and adaptive to the competitive environment.

Generate operational knowledge module will query the dimension bucket analysis table (Table 5) by (a) first updating the table lop attribute with AND or OR values that are needed to format the business rules structure, and (b) then display the knowledge in the form of business rules. The following list outlines the insight-driven business rules knowledge pertaining to the Borrower dimension:

Empl Dur = greater than 2 years AND
Empl Type = W-2 AND
Rent Pymt Dur = greater than 3 years
THEN Borrower Traits = High

Empl Dur = less than 2 years AND
Empl Type = W-2 OR
Empl Type = Self AND
Rent Pymt Dur = greater than 3 years OR
Rent Pymt Dur = less than 3 years
THEN Borrower Traits = Low

The following list outlines the insight-driven business rules knowledge pertaining to the Financial dimension:

Credit_Score = greater than 600 AND
DTI = less than 40% AND
House Type = Primary
THEN Financial Traits = High

Credit_Score = less than 600 AND
DTI = less than 40% AND
House Type = Investment OR
House Type = Primary
THEN Financial Traits = Low

The following list outlines the insight-driven business rules knowledge pertaining to the Location dimension:

Crime_Rate = Medium OR
Crime_Rate = High AND
Hospital = Yes OR
Hospital = No AND
Park = Yes OR
Park = No AND
school_dist = Glendale OR
school_dist = Parkview
THEN Location Traits = High

Crime_Rate = Low OR
Crime_Rate = Medium AND
Hospital = No AND
Park = Yes OR
Park = No AND
school_dist = Republic OR
school_dist = Shawnee Mission
THEN Location Traits = Low

The following list outlines the insight-driven business rules knowledge pertaining to the Property dimension:

HOA = Greater than 500 OR
HOA = Less than 500 AND
Pool = Yes AND
bath = 1 OR
bath = 2 AND
bedrooms = 3 OR
bedrooms = 5 OR
bedrooms = 2
THEN Property Traits = High

HOA = Greater than 500 OR
HOA = Less than 500 AND
Pool = Yes OR
Pool = No AND
bath = 2 AND
bedrooms = 5 OR
bedrooms = 3
THEN Property Traits = Low

Once the associations for each dimension have been outlined, a collective business rules operational insight can be outlined that brings it all together as shown below.
IF borrower traits = High AND
Location quality = High AND
Financial traits = High AND
Property quality = High
THEN Mortgage Revenues High with Mortgage count 13

IF borrower traits = Low AND
Location quality = Low AND
Financial traits = Low AND
Property quality = Low
THEN Mortgage Revenues Low with Mortgage count 8

4.2. Impact on Business Process Operations

There are number of ways a mortgage lending business can incorporate operational insights into their business operations. One approach could be to identify the relevant business process activities associated with the dimension attributes and then make adjustments to improve process activities operations as shown in Figure 2. Borrower traits play a key part in every mortgage decision. For instance, the mortgage lending business generally focuses on high quality borrowers' traits to ensure more successful mortgages. But from a bucketed insight perspective, the lending business could also identify borrower traits associated with low success rates and then develop targeted strategies through relevant business process activities to improve these traits and achieve more successful mortgage outcomes.

A second approach may involve developing guidelines for each bucket insight and set separate mortgage rates for each bucket. For instance, set a different mortgage rate for those borrowers where the mortgage revenues are in the high bucket compared to the low bucket. It is also possible for the business to have mortgage rates for some combination of high and low bucket insights.

The third approach could be when the business incorporates such operational insights into their existing operational guidelines. For instance, suppose the lending business may have mortgage guidelines like below for determining how mortgages will be offered:

Rule 1:
IF Credit risk is high AND
Down payment is less than 20% AND
Capacity risk is high AND
Loan to value is 100% AND
Loan requested is greater than $75,000
THEN Customer loan is reject

Rule 2:
IF Credit risk is Low AND
Down payment is more than 20% AND
Capacity risk is Low AND
Loan to value is less than 80% AND
Loan requested is greater than $95,000
THEN Customer Loan is approve 3.5% APR

The bucket derived operational insights can be now added to the existing mortgage guidelines as follows:

Rule 1 (modified):
IF Credit risk is high AND
Down payment is less than 20% AND
Capacity risk is high AND
Loan to value is 100% AND

Loan requested is greater than $75,000 AND
Borrrower traits is low AND
Financial traits is low AND
Location traits is low AND
Property traits is low AND
THEN Customer loan is reject

Rule 2 (modified):
IF Credit risk is Low AND
Down payment is more than 20% AND
Capacity risk is Low AND
Loan to value is less than 80% AND
Loan requested is greater than $95,000 AND
Borrrower traits is high AND
Financial traits is high AND
Location traits is high AND
Property traits is high AND
THEN Customer Loan is approve 3.5% APR

5. CONCLUSIONS

Business process intelligence is all about providing insights and improving efficiency of business processes within an organization. By providing up-to-date insights to the right people at the right time improves the timeliness and quality of decisions needed to remove bottlenecks in any business process. As organizations focus on making smart and intelligent decisions to compete successfully, a key aspect of proper business intelligence deployment is an assessment of whether certain business process measures guarantee success on a continual basis.

This paper provides an approach to develop bucket driven insights in the form of operational business rules that provide guidance for ensuring the continued success of the business processes. Compared to traditional business process analytics, bucket driven insights provide a better assessment of business operations. Leveraging buckets to group and deliver analytics adds greater depth to enhancing business performance.

Any business can categorize its insights into multiple buckets based on relevancy. For instance, the retail business can create buckets on customer and product insights with respect to order fulfillment business process. Also, the airline business can utilize bucket analysis to sell seats with respect to flight reservation business process. Further research is ongoing to enhance the approach by having more bucket categories and embedding more complexity in bucket analysis involving trends, associations, and so on as a way to fine tune business process operations.

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APPENDIX A

```
create table borrower
(BID int constraint borrower_pk primary key,
empl_dur varchar2(50),
empl_type varchar2(50),
rent_pymt_dur varchar2(50));

insert into borrower
values(1,'less than 2 years','Self','less than 3 years');
insert into borrower
values(2,'greater than 2 years','W-2','greater than 3 years');
insert into borrower
values(3,'greater than 2 years','W-2','less than 3 years');
insert into borrower
values(4,'greater than 2 years','Self','greater than 3 years');
insert into borrower
values(5,'less than 2 years','W-2','greater than 3 years');

create table financial
(FID int constraint financial_pk primary key,
Credit_Score varchar2(50),
House_type varchar2(50),
DTI varchar2(50),
Liabilities varchar2(50));

insert into financial
values(1,'less than 600','Investment','less than 40%', 'less than 15%');
insert into financial
values(2,'greater than 600','Primary','less than 40%', 'less than 15%');
insert into financial
values(3,'less than 600','Primary','less than 40%','greater than 15%');
insert into financial
values(4,'greater than 600','Investment','less than 40%', 'less than 15%');
insert into financial
values(5,'less than 600','Investment','greater than 40%', 'greater than 15%');
insert into financial
values(6,'less than 600','Primary','greater than 40%', 'greater than 15%');
insert into financial
values(7,'greater than 600','Primary','less than 40%', 'greater than 15%');

create table location
(LID int constraint location_pk primary key,
Park varchar2(3),
Crime_Rate varchar2(10),
School_Dist varchar2(50),
Hospital varchar2(3));

insert into location
values(1,'No','Low', 'Kickapoo','Yes');
insert into location
values(2,'Yes','Medium', 'Parkview','No');
insert into location
values(3,'Yes','Medium', 'Glendale','No');
insert into location
values(4,'Yes','Low', 'Republic','No');
insert into location
```

```
values(5,'No','Low', 'Nixa','Yes');
insert into location
values(6,'Yes','High', 'Oak Park','Yes');
insert into location
values(7,'Yes','Medium', 'Oak Park','Yes');
insert into location
values(8,'No','Medium', 'Blue Valley','No');
insert into location
values(9,'No','High', 'Parkview','No');
insert into location
values(10,'No','Medium', 'Shawnee Mission','No');


create table property
(PID int constraint property_pk primary key,
Bedrooms int,
Bath number(2,1),
Pool varchar2(5),
HoA integer);

insert into property
values(1,3,2,'Yes',800);
insert into property
values(2,4,2.5, 'Yes',600);
insert into property
values(3,5,3,'Yes',500);
insert into property
values(4,3,2, 'No',450);
insert into property
values(5,3,2.5, 'Yes',380);
insert into property
values(6,3,2, 'No',0);
insert into property
values(7,4,3,'Yes',98);
insert into property
values(8,2,2, 'Yes',110);
insert into property
values(9,2,1, 'No',0);
insert into property
values(10,5,3.5, 'Yes',150);

create table mortgage_fact
(MID int constraint mortgage_fact_pk primary key,
BID int constraint mortgage_fk1 references borrower,
FID int constraint mortgage_fk2 references financial,
LID int constraint mortgage_fk3 references location,
PID int constraint mortgage_fk4 references property,
NumSold int);

insert into mortgage_fact values(1,1,1,1,10,10);
insert into mortgage_fact values(2,1,4,2,9,15);
insert into mortgage_fact values(3,3,7,3,8,20);
insert into mortgage_fact values(4,4,5,4,7,10);
insert into mortgage_fact values(5,5,6,5,6,15);
insert into mortgage_fact values(6,1,4,6,5,20);
insert into mortgage_fact values(7,1,3,7,4,10);
insert into mortgage_fact values(8,3,3,8,3,15);
```

```
insert into mortgage_fact values(9,4,2,9,2,20);
insert into mortgage_fact values(10,5,1,10,1,10);
insert into mortgage_fact values(11,5,3,1,10,15);
insert into mortgage_fact values(12,2,2,2,9,20);
insert into mortgage_fact values(13,5,1,3,8,10);
insert into mortgage_fact values(14,4,4,4,7,15);
insert into mortgage_fact values(15,5,6,5,6,20);
insert into mortgage_fact values(16,1,1,6,5,10);
insert into mortgage_fact values(17,5,4,7,4,15);
insert into mortgage_fact values(18,3,7,8,3,20);
insert into mortgage_fact values(19,4,1,9,2,25);
insert into mortgage_fact values(20,5,3,10,1,10);
insert into mortgage_fact values(21,1,2,1,10,15);
insert into mortgage_fact values(22,2,4,2,9,20);
insert into mortgage_fact values(23,3,2,3,8,25);
insert into mortgage_fact values(24,1,4,4,7,10);
insert into mortgage_fact values(25,5,1,5,6,15);
insert into mortgage_fact values(26,2,2,6,5,20);
insert into mortgage_fact values(27,5,4,7,4,15);
insert into mortgage_fact values(28,4,7,8,3,20);
insert into mortgage_fact values(29,5,2,9,2,25);
insert into mortgage_fact values(30,5,4,10,1,25);

commit;
```