Working with Different Types of Data		
Keywork	Explanation	Example
!		
'		df.select(count("StockCode"))
	select count	spark.sql("SELECT count(StockCode) FROM dfTable")
!		df colort/countDistinct/"StockCodo"\\
count distintct	count distintct	df.select(countDistinct("StockCode"))  spark sal("SELECT count(distinct(StockCode)) FROM dfTable")
Count distilled	count distintet	spark.sql("SELECT count(distinct(StockCode)) FROM dfTable")  df.select(approx count distinct("StockCode", 0.1))
!		spark.sql("SELECT approx_count_distinct(StockCode) FROM
approx count distinc	  approx_count_distinct	dfTable")
αρριολ_σσα	approx_count_distinct	df.select(first("StockCode"), last("StockCode"))
· ·		spark.sql("SELECT first(StockCode), last(StockCode) FrOM
first last	first last	dfTable")
11130.022	instruction of the control of the co	
· ·		df.select(min("Quantity"), max("Quantity"))
min max	min max	spark.sql("SELECT min(Quantity), max(Quantity) FrOM dfTable")
		df.select(sum("Quantity"))
sum	sum	spark.sql("SELECT sum(Quantity) FrOM dfTable")
sumDistinct	sumDistinct	df.select(sumDistinct("Quantity"))
		df.select(avg("Quantity"))
avg	avg	spark.sql("SELECT avg(Quantity) FROM dfTable")
selectExpr	selectExpr	dfselectExpr( "total_purchases/total_transactions")
		df.select(var_pop("Quantity"), var_samp("Quantity"),
		stddev_pop("Quantity"), stddev_samp("Quantity"))
,   !		spark.sql("""
var_pop var_samp		SELECT var_pop(Quantity), var_samp(Quantity),
stddev_pop		stddev_pop(Quantity), stddev_samp(Quantity)
stddev_samp	Variance and Standard Deviation	FROM dfTable""")
skewness kurtosis	skewness and kurtosis	df.select(skewness("Quantity"), kurtosis("Quantity"))
		df.select(corr("InvoiceNo", "Quantity"), covar_samp("InvoiceNo",
corr covar_samp		"Quantity"),
covar_pop	Covariance and Correlation	covar_pop("InvoiceNo", "Quantity"))  df.agg(collect_set("Country"), collect_list("Country"))
agg collect_set list	Aggregating to Complex Types	df.agg(collect_set("Country"), collect_list("Country"))  df.groupBy("InvoiceNo", "CustomerId").count()
,		groupBy("InvoiceNo", "Customeria").count() spark.sql("SELECT count(*) FROM dfTable GROUP BY InvoiceNo,
groupBy	Grouping	CustomerId")
groupsy	Grouping	df.groupBy("InvoiceNo").agg(
,		count("Quantity").alias("quan"),
groupBy express	Grouping with Expressions	expr("count(Quantity)"))
Broads, cut.	Grouping with Exp. 655.615	df.groupBy("InvoiceNo").agg("Quantity"->"avg", "Quantity"-
,		>"stddev_pop")
,		spark.sql("SELECT avg(Quantity), stddev_pop(Quantity), InvoiceNo
maps	Grouping with Maps	FROM dfTable GROUP BY InvoiceNo")
	Windows functions	·
1		val rolledUpDF = dfNoNull.rollup("Date",
1		"Country").agg(sum("Quantity"))
1		.selectExpr("Date", "Country", "`sum(Quantity)` as
1		total_quantity")
1		.orderBy("Date")
1	rollup is a multidimensional aggregation that performs a	
rollup	variety of group-by style calculations	rolledUpDF.where("Country IS NULL")
ı		
,	Cube (ie rollup to a level deeper) - Rather than treating	
,	elements hierarchically, a cube	dfNoNull.cube("Date", "Country").agg(sum(col("Quantity")))
cube	does the same thing across all dimensions.	.select("Date", "Country", "sum(Quantity)").orderBy("Date")
,  ·	Pivots make it possible for you to convert a row into a	104015Data annun ("data") nivet("Country") cum()
pivot	Column User-Defined Aggregation Functions	val pivoted = dfWithDate.groupBy("date").pivot("Country").sum()
<u> </u>	User-Defined Aggregation Functions	